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The Influence of the Length of the School Day on Grade 11 NJ HSPA Scores

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ABSTRACT

THE INFLUENCE OF THE LENGTH OF THE SCHOOL DAY ON
GRADE 11 NJ HSPA SCORES

This study examined the strength and the direction of the relationship between the length of the school day and Grade 11, 2011 New Jersey High School Proficiency Assessment (HSPA) scores found on the New Jersey Department of Education (NJDOE, 2012a) website. Student achievement scores on the Grade 11, 2011 HSPA in Language Arts and Mathematics were analyzed separately. Analyses were conducted using simultaneous regression and hierarchical multiple models. All student data explored in this study pertained to 98,218 first-time, Grade 11 students (NJDOE, 2011c) enrolled in 326 public high schools in districts designated by District Factor Groups A-J (NJDOE, 2012a) comprehensive high schools located in the state of New Jersey during the 2010-2011 academic school year. The results of the study revealed that using the length of the school day as an independent variable to predict the dependent variable of student 2011 NJ HSPA mathematics passing percentage accounted for 1.8 percent in the variance. For Language Arts, however, the length of the school day was found to have a non-statistically significant relationship with the original dependent variable (the HSPA passing percentage).

The sample was taken from the NJDOE, NJ School Report Card 2011 (NJDOE, 2012a) representative of a proportional random sample of the state's district composition. Recommendations for policy, practice, and future research were explored.

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The mode by which the inevitable comes to pass is effort.
– Oliver Wendell Holmes, Jr. (1841-1935); Associate Justice, U.S. Supreme Court

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DEDICATION

Fortunately, I was given the gift of a good head start in life. My parents, Tom and Jay, always instilled in me the importance of obtaining an education. My mother nurtured and encouraged most goals and dreams, always pushing for a way forward but reminding me of the virtues of honesty and humility. Most importantly, I must thank my beloved Uncle John and Aunt Jean Graziano who showered me with unconditional love and devotion beyond a child's fancy (from my earliest memories); they provided me with a solid sense of security, fun, and joy of life. Hard work garners success, a mantra I learned early and emulated throughout my life, helped me to reach my potential. I would be remiss if I did not mention my childhood parish, American Martyrs, Bayside, New York, because it was there that a wealth of wonderful parishioners became my nucleus of friends, role models, and extended family that cultivated my development. I am deeply grateful to all my past employers, bosses and colleagues who praised my work, instilled confidence in me, and rewarded my accomplishments. To my best friends, Joyce, Gail, Lynne, Lyn, Marylou, Donna, and Danielle, who cheered me on whenever the going got rough, thanks for listening. For WB, thank you for all your support over the years; I appreciate your cheerful attitude and willingness to help that never seemed to falter. To my former professors, acquaintances, and anyone else who has made a positive contribution in my life, I say thank you. To my siblings, Anita, Phil, and Joe, who have always encouraged my academic pursuits and are just as proud of this work as I am, thank you. To my students at New Brunswick High School, I wish for you the very best in life, which begins with a solid education and a love of learning. Primarily to my husband, John, I dedicate this work to you for your unwavering love, patience, and encouragement to pursue this challenge; without your full support, the end of this journey could never have been reached.

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CHAPTER I

INTRODUCTION

Background

There are no shortages of policy proposals for changes on the amount of time students spend in school. Gaining momentum in legislative circles is the idea that a longer school day and/or year will produce increased student achievement as measured by state mandated standardized tests. The recommendations for reforming the length of the school day or length of the school year engender controversy and debate. From a historical perspective, some believe the myth that it was the United States agrarian society that formed the basis of the school calendar of 180 days and the approximately six and a half hours a day spent in school (Cuban, 2008, p. 242). Actually it was the evolving, elite society that sprang up in the United States during the early 20th Century that desired to escape from the summer heat and advocated to spend time with their children to vacation over the summer months that influenced the length of the school day and the school calendar year (Cuban, 2008; Silva, 2007, as cited in Patall, Cooper, & Batts-Allen, 2010). Today, it is the middle class and affluent parents who are the biggest proponents of maintaining the existing school calendar, as well as industrial sectors that profit from summer vacations (Cuban, 2008; Silva, 2007, as cited in Patall et al., 2010).

> Affluent parents are more divided in their reaction to potential expansions of school schedules because they have often already invested time and money in placing their children in structured, supervised out-of-school activities to complement the content and schedule of school (Gabrieli, 2010, p. 42).

The seminal work of Carroll (1963) first defined variables related to learning. It was Carroll (1963) who espoused that time was the most critical school variable connected to learning academic content but he also proposed that student aptitude, teacher characteristics, and the time engaged on task would be reflected in learning achievement. Bloom (1974) built his philosophy on Carroll's learning model. Bloom (1974) cited Carroll's model of learning time.

In the Carroll (1963) model of school learning, the basic thesis is that *time* is a central variable in school learning and that students differ in the amount of time they need to learn a given unit of learning to some set criterion. Carroll defined *aptitude* as the amount of time needed by a student to reach the criterion, and he stated that the amount of time needed by each student could be predicted by an appropriate aptitude test. He contended that if the student were given the amount of time he or she needed and if he or she persevered until this amount of time had been devoted to the learning task, the student would reach the criterion level of achievement. (Bloom, 1974, p. 683).

Since the initial mention of school time and the learning model proposed by Carroll (1963), school reforms have become cloaked in the belief that more time equals more achievement. In recent times policymakers, pundits, and education bureaucrats claim that more time in school translates into increased test scores that somehow affects the ability of the U.S. workforce to better compete globally. The policy intervention of more time in school derives from production-function theory—the more one puts in, the more one gets out. The theoretical framework of this line of research is based upon input-output models. Nonetheless, Zhang & Chen (2008) stated, "Education is different from other kinds of products: its output is not a change in the 'physical properties' of students. The output of education is the increase in knowledge, qualification, attitudes, perceptions, emotions, and skills that students receive from this kind of production process" (pp. 206, 207). Zhang & Chen (2008) also recognized that "it is, however, difficult to quantify the increase in knowledge, qualification, and skills" (pp. 206-

207). Ayers (2013) disparaged the pillars of current “school reform” and has been supporting the reality that educational agendas are flawed; he jolts us into acknowledging that the three pillars that form the basis of current reforms are just “a seductive, but wholly inaccurate metaphor: education is a commodity like any other—a car or a refrigerator, a box of bolts or a screwdriver” (p. 53).

In reference to education productivity, a powerful message is relayed by Childress (2012) and supported by West (2012, p. 41) when referencing Hanushek’s (2008) work on the link between student performance and economic growth: In 2008 the Stanford economist Eric Hanushek developed a new way to examine the link between a country’s GDP and the academic test scores of its children. He found that if one country’s scores were only half a standard deviation higher than another’s in 1960, its GDP grew a full percentage point faster in every subsequent year through 2000 (Childress, 2012, p.77).

Using Hanushek’s methods, McKinsey & Company estimated that if the United States had closed the education achievement gap with better-performing nations, GDP in 2010 could have been 8% to 14%—$1.2 trillion to $2.1 trillion—higher. The report’s authors called this gap “the economic equivalent of a permanent national recession” (Childress, 2012, p. 77). In the past there was a focus on the numbers of years of student schooling that predicted economic growth rates. Economists such as Hanushek (2008) now foresee that measured student cognitive skills are the indicator that will make the difference in economic growth (West, 2012, p. 41). Another finding related to the work of economists Eric Hanushek and Ludger Woessmann is the following:

> They found that both the share of a country's students performing at a very high level and the share performing above a very low level appear to contribute to

> economic growth in roughly equal amounts, suggesting that there is no clear economic rationale for policymakers to focus exclusively on improving performance at the top or the bottom of the ability distribution (West, 2012, p. 41).

Because policymakers, and some education pundits, might feel that imposing a longer school day and school year on the most socioeconomically disadvantaged will have an impact on the economy, administrators and the public need to carefully resist the temptation of a blanket endorsement of such policies. According to economists and educational researchers, quality not quantity in education is the imperative factor. “More time in schools can be costly and so a focus on how the extra time is used is critical” (Aronson, Zimmerman, & Carlos, 1998, p. 3; Walberg, 1988, p. 85).

In this study, I examined school inputs to determine the influence of the length of the school day on Grade 11 NJ High School Proficiency Assessment (HSPA) scores in Language Arts (LA) and Mathematics (MA) for the year 2011. Since production function involves mathematical calculations, statistical analyses of inputs (school factors) were specified to assess the amount of variance exerted on the output measure (NJ HSPA scores).

The controversy over more school time “has been fueled by international comparisons showing that students in other industrialized nations have higher achievement test scores than students in the United States” (Gonzales, Partelow, Pahlke, Jocelyn, Kastberg, Williams, 2004, as cited in Patall et al., 2010, p. 402). The Organization for Economic Cooperation and Development (OECD, 2012) reinforced contrasts by stating that “governments are paying increasing attention to international comparisons as they search for effective policies that enhance individuals’ social and economic prospects, provide incentives for greater efficiency in schooling, and help mobilize resources to meet rising demands" (p. 3). Tienken (2013) analyzed PISA and TMMS test scores and asserted that it is "naïve to look only at the aggregated results" (p. 57) and raised the issue of test score compatibility between groups; "the groups must be comparable in terms of the factors that influence standardized test scores" (Tienken, 2013, p. 57). An international test score analysis showed a significant difference between groups because of the following:

> (a) selective sampling on the part of some countries, (b) negotiating questions used on the test and the relationship to those questions and a country's curriculum sequence, and (c) lower overall childhood poverty percentages in some countries compared to the 23% child poverty in the United States (Bracey, 2006; Kids Count, 2010, as cited by Tienken, 2013, p. 57).

According to Tienken and Orlich (2013), school reforms usually have been introduced and fueled by domestic or international crises such as most recently the 2008 severe economic downturn (p. 26). For example, Tienken & Orlich (2013) emphasized that President Obama and Secretary of Education Arne Duncan "perpetuate the mythology of education crisis with their frequent calls for a 'Sputnik moment' in education" (p. 20). "Sputnik is a manufactured crisis" (Berliner and Biddle, 1995, as cited in Tienken & Orlich, 2013, p. 21) and has not been based upon facts or reality.

U.S. Department of Education Secretary Arne Duncan stated the following at a 2009 Congressional hearing:

> Our students today are competing against children in India and China. Those students are going to school 25 to 30 percent longer than we are. Our students, I think, are at a competitive disadvantage. I think we're doing them a disservice

(Hull, 2012, p. 1).

According to data from the OECD and the World Data on Education, students in China and India are not required to spend more time in school than most U.S. students (Hull & Newport, 2011). The data showed that a number of countries that required fewer hours of instruction outperformed the United States, whereas the United States performed as well as or better than some other countries that required more hours of instruction (Hull & Newport, 2011). Furthermore, Tienken (2013) highlighted that “the public school systems in wealthy Chinese cities are not representative of the Chinese system, nor are they like U.S. public school systems” (p. 57).

Billions of dollars have been channeled to states that implemented internationally benchmarked practices (Shea & Ceprano, 2013). At the U.S. federal level, President Barack Obama’s administration funded and promoted growing educational reforms based on “the link between education and national competitiveness” (West, 2012, p.37). One such recent example, Race to the Top (RTTT), a federally funded education program, was formed to encourage states to adopt internationally benchmarked practices to turn the tide on America’s lowest-performing schools (OECD, 2010b, p. 228). Speculative speeches and philosophical rhetoric by U.S. politicians and government agencies have been grounded in the desire to push for higher-performing educational systems to drive achievement and maintain a higher global competitive edge (Bieber & Martens, 2011).

The OECD (2010b) listed Canada, Finland, Shanghai-China, and Singapore as high-performing education systems even though they admitted that “the very best education institutions can be found in the United States, at every level from the elementary school to the research university and that the United States educates for the high level of innovation demonstrated in the economy" (p. 229).

The OECD (2012) has considered itself an authoritative resource for providing relevant information about the state of education globally. Through its publications the OECD has exerted influence over global educational policy. The OECD has supported policy sharing and transnational communication as a way to improve global educational efforts (Voegtl, Knill, & Dobbins, 2011. p. 78). Because the OECD has no direct power over nations, it has relied on the promotion of convergence**.** "Convergence research refers to the change of policy features" (Dobbins, 2008, p. 70) and investigates the "tendency of policies to grow more alike, in the form of increasing similarity in structures, processes, and performances" (Drezner, 2001 p. 53). This confirms that the OECD is a powerful entity that influences global education policies by disseminating information on purported best practices (Bieber & Martens, 2011; Voegtle et al., 2011). However, before using the policy convergence theory of transnational communication and information sharing, Bieber et al. (2011, p. 102) emphatically proposed that to adopt changes in one's own nation based on what other nations or states do requires policymakers to use empirical research to ensure that decisions result in student achievement gains. Educational administrators need to determine if policy reforms, particularly as they apply to changes in allotted school time, will help alleviate the problems identified by education bureaucrats. Can one such problem, lower than desired numbers of high school students passing mandated state tests of academic skills and knowledge on high stakes high school exit exams, be solved or reduced by lengthening the school day or school year?

Gabrieli (2011) claimed that "the traditional school schedule has been under challenge by experts and reformers for at least thirty years" (p. 44). Beginning with the 1983 National

Commission on Educational Excellence in their report entitled *A Nation at Risk*, the assertion that spending more time in school would yield greater test achievement has been repeatedly voiced. “Because there has been a widespread failure among U.S. high schools to meet academic goals, particularly for high-poverty students, the movement to adopt longer school days beyond six and a half hours per day and a longer than 180 day school calendar year grows increasingly popular each year” (Gabrieli, 2011, p. 43) However, Gabrieli (2010) also emphasized that “simply expanding time . . . at schools is not a silver bullet for success” (p. 40). Nevertheless, “neo-institutional approaches tend to explain the adoption of innovations not as a way of more effectively addressing an internal situation, but rather as a response to external pressures and influences or as a way to gain legitimacy” (Warren & Kulick, 2007, p. 215). The TIME Act has been re-introduced by several U.S. Senators as recently as April 2011 to support school grant programs that in essence implemented a longer school day or a longer school year (Farbman, 2011, p. 5). Among some of the more recent policy changes to school calendars or daily time spent in school included the following: thirty states launched 300 initiatives between 1991 and 2007 for more school time directed at high poverty and high-minority schools, an additional 50 states used extended-day programs between 2000 and 2008, Delaware proposed an additional 140 instructional hours through either a longer day or longer school year, and Ohio purported to add 20 days to the school year (Patall et al., 2010). Despite all these initiatives little consensus exists on whether the length of the school day and school year enhances student achievement (Patall et al., 2010).

The No Child Left Behind Act (NCLB) was signed into law by President George Bush in 2002 (NCLB: A Desktop Reference, 2002, p. 9). It was designed to provide access and a quality education for all children. President Bush suggested that we needed a way to demonstrate to both parents and teachers that children could read and write. This paved the way for using testing to account for results and as the primary indicator of how a school was performing. As a component of the reauthorization of the Elementary and Secondary Education Act (ESEA), Congress envisioned new policies for "increasing learning time for low-performing students" (Farbman, 2011, p. 5).

The desire to improve high school student performance remains at the forefront of policy-makers and education bureaucrats. Bracey (2007) espoused that he has "seen nothing to suggest that NCLB has improved schools" (p. 324). Bracey (2007) further advised that "I don't think researchers are snookered by statistics so much as they are by the overwhelming negativity surrounding public schools. People lie in wait for chances to prove the schools are terrible" (p. 324). "Year-round schooling ought to improve achievement, but so far the data have not shown any great impact at all" (Bracey, 2007, p. 326).

Statement of the Problem

The results from the empirical literature about the influence of length of school day on student achievement have been mixed. Furthermore, little relational, quantitative, explanatory research exists on the influence of the length of the school day on Grade 11 New Jersey HSPA student achievement scores. Patall et al. (2010) conducted an extensive review of the literature in their meta-analysis on an extended school year (EY) and extended school day (ED) and located all related studies from 1985-2010. Many of the studies reviewed were termed "generally weak for making causal inferences" (Patall et al., 2010, p. 1). Also, most of the studies conducted have been at the elementary or pre-school grade levels. The literature search by Patall et al. (2010) revealed no studies conducted on EY or ED on high-stakes test scores (as the dependent variable) for high school students in the state of New Jersey. Therefore, a quantitative study analyzing the influence that length of the school day and what influence, if any, it has on high-stakes test results in New Jersey is warranted.

Purpose and Research Questions

My purpose for this study was to explain the influence of length of school day for students, reported in minutes, on the Grade 11, 2011 NJ HSPA high school exit exam in Language Arts (LA) and Mathematics (MA).

The overarching research question used in this study asks: What is the influence of length of school day on the Grade 11, 2011 New Jersey state-mandated High School Proficiency Assessment (HSPA) scores when controlling for student, school, and staff variables?

Subsidiary Research Questions

Research Question 1: What is the strength and direction of the relationship between length of school day on the Grade 11, 2011 New Jersey state-mandated High School Proficiency Assessment (HSPA) scores in Language Arts when controlling for student, school, and staff variables?

Research Question 2: What is the strength and direction of the relationship between length of school day on Grade 11, 2011 New Jersey state-mandated High School Proficiency Assessment (HSPA scores) in Mathematics when controlling for student, school and staff variables?

Null Hypotheses

Null Hypothesis 1: No statistically significant relationship exists between length of school day and school score performance on the 2011 Grade 11 NJ HSPA for the 326 New Jersey high schools as measured by Proficient or above.

Null Hypothesis 2: No statistically significant relationship exists between length of school day and the Language Arts school score performance on the 2011 Grade 11 NJ HSPA for the 326 New Jersey high schools as measured by proficient or above.

Null Hypothesis 3: No statistically significant relationship exists between length of school day and the actual Mathematics school score performance on the 2011 Grade 11 NJ HSPA for the 326 New Jersey high schools as measured by Proficient or above.

Independent Variables: The NJ School Report Card

The independent variables for this study were derived from the NJ 2011 School Report Card. Education bureaucrats at the New Jersey Department of Education collect data on various aspects of school and district operations and publish those data in a yearly report card. The NJ school report card variables used in this study (See Table 1), and found in the extant literature, to influence student achievement at the high school level include the following:

Table 1

Selected Staff, Student, and School Predictor Variables

Selected Staff, Student and School Predictor Variables		
Staff Variables	**Student Variable**	**School Variables**
Percentage of Staff with Master's Degree or Higher	Student Mobility Rate	Length of School Day in Minutes
	Student Attendance Rate	
Faculty Mobility Rate	Percentage of Students Eligible for Free or Reduced Lunch (SES)	
Faculty Attendance Rate	Percentage of Students with Limited English Proficiency	School Size
	Percentage of Students with Disabilities	

Student Achievement Scores
Grade 11 NJ HSPA 2011

Unlike some variables, the length of the school day and instructional time can be directly altered or influenced by school districts (Eren & Millimet, 2007; Walberg, 1988).

Dependent Variable: The Grade 11 NJ HSPA

The dependent variable in this study was student achievement on the Grade 11 NJ HSPA 2011. NJ HSPA scores are reported as proficiency percentages under the categories of Partially Proficient, Proficient, and Advanced Proficient for school, district and state on NJ Report cards for all students tested in the content areas of Language Arts and Math. Scores for Language Arts Literacy (LAL) and Mathematics (MA) were used for 92,218 first-time 11th grade students (NJDOE, 2011c); the numerical scores associated with the NJDOE include three major categories: Partially Proficient (<200); Proficient (200-249); and Advanced Proficient (250-300) for both Language Arts and Mathematics, which are reported separately. The percentage of Proficient and above is the measurement value of the dependent variable used in this study (NJDOE, 2009).

Significance of the Study

"Education is the currency of the Information Age—no longer just a pathway to opportunity and success, but a pre-requisite . . . In this kind of economy, countries who out-educate us today will out-compete us tomorrow" (Obama 2008 as cited in Darling-Hammond, 2009, p. 213 and Tienken, 2013 p. 56). "Unwavering support for excellence in teaching and school leadership is perhaps the key element of the policies and practices that drive high-performing education systems, such as those in Canada, Finland, Japan, Shanghai-China, and Singapore" (OECD, 2010b, p. 230). Given the varied methods researchers have used to examine the relationship between extended school time and achievement as well as inadequate reporting of the necessary information to calculate effect sizes in some cases, it is difficult to assess the magnitude of relationship between extending school time and academic achievement (Patall et al., 2010, p. 427).

The unit of analysis for my study was at the school level. To increase the knowledge base on what was analyzed and captured in the meta-analysis conducted by Patall et al. (2010), this study added to the literature by running hierarchical regression analyses on test data reported by the NJDOE high-stakes testing. I conducted a study to determine the variance on Grade 11, 2011, HSPA scores that can be explained by the length of the school day for 326 high schools in New Jersey. Different from other studies surrounding the school day length was that the school day was analyzed separately by school day length and separately by SES strata (and analyzed with attendance as a covariate or without). To apply the findings at the principal or district level, I calculated passing percentage changes between the short, medium, and long day lengths which would be useful for making decisions at the building level.

Limited studies have been conducted at the high school level without reporting the significance of the influence of the length of the school day/school year. Bishop, Worner, & Weber (1988) conducted a cohort study and a survey on only one rural high school in Virginia (which also included grade 8 students); furthermore, regarding this study according to Patall et al. (2010), "The sample between cohorts made it impossible to tell what the actual sample size would have been" (E. Patall, personal communication, March 13, 2013). Green (1998) and Sims (2008) (as cited in Patall et al., 2010) also conducted studies on the length of the school day at the high school level, but the sample sizes were small and effect sizes were not reported. All the other studies conducted on length of the school day mentioned in the literature and in Patall et al. (2010) meta-analyses were directed at the elementary, middle, kindergarten, and pre-school grades with mixed effect size reported. The results of this study add to the existing knowledge dynamic and can help administrators make decisions about the factors that influence student achievement and in particular the establishment of effective policies designed to restructure schools around the variable−length of the school day because effect sizes are reported. Education is an expensive commodity, and the more school policy decisions are formulated based on research rather than rhetoric, the more likely funding will be spent toward achieving increased student results.

> The point is that when the schools are being criticized, vulnerable school administrators have to respond. The quickness of the response and the nature of the response depend upon the nature and strength of the criticism. Since 1900 this pattern of criticism and response has produced some desirable and some undesirable educational changes, but the

> real point is that this is an inadequate and inappropriate basis for establishing sound educational policy (Callahan, 1966, p. vii).

Limitations/Delimitations of the Study

According to Muijs (2005), in order to analyze teacher effectiveness, school effectiveness and student effectiveness, one needs to sufficiently control for other variables that may affect outcomes (p. 65). In this study, the other variables analyzed from the NJ 2011 HSPA report card results included (a) faculty attendance rate, (b) faculty mobility rate, (c) percentage of faculty with master's degree or higher, (d) student attendance rate, (e) student mobility rate, (f) percentage of students eligible for free or reduced lunch, (g) percentage of students with limited English proficiency, (h) percentage of students with disabilities, (i) length of school day in minutes, and (j) school size. Because "non-experimental research is frequently an important and appropriate mode of research in education" (Johnson 2001, p. 3), I conducted a non-experimental, cross-sectional, explanatory study. This study will address only the length of the school day on Grade 11 2011 NJ HSPA scores.

This explanatory study applied correlations from data collected from one point and time; that in and of itself limits the study.

Furthermore, this study is limited to the New Jersey secondary schools District Factor Groups "A-J" and as such the results may not be projected to other high school student groups.

Assumptions

It was assumed that the report card data housed and reported on the NJDOE website is accurate. Further, it was assumed that the data transferred from the NJDOE (2012a) Excel spreadsheets were accurately transposed and imported into the statistical analysis software, Statistical Package for the Social Sciences (SPSS). Also it was assumed that test scores and reports of the length of the school day in New Jersey for the 2011 school year revealed significant relationships and accurate variances that can be generalized to other states.

Definition of Terms

Accountability. The federal No Child Left Behind Act (NCLB) requires all states to establish standards for accountability for all schools and districts in their states. The accountability system looks at the degree to which students across schools and districts are mastering the state standards. NCLB has set the goal of 100% proficiency by the year 2014, with states setting incremental benchmarks. (NJDOE, 2011d).

Achievement Gap. Refers to the disparity in academic performance between groups of students. The achievement gap shows up in grades, standardized-test scores, course selection, dropout rates, and college-completion rates, among other success measures. It is most often used to describe the troubling performance gaps between African-American and Hispanic students at the lower end of the performance scale, and their non-Hispanic White peers and the similar academic disparity between students from low-income families and those who are better off.

Adequate Yearly Progress (AYP). NCLB mandates that each state measure the progress made toward reaching the goal of 100% proficiency for all students in language arts and mathematics. Each state implements targets, or benchmarks, to ensure this goal is achieved by the year 2014. AYP is a complicated measuring tool with many components. Districts that fail to meet AYP targets are held accountable (NJDOE, 2011a).

Assessment. Assessments ascertain student skills and knowledge. The statewide assessment system comprises state tests that are designed to measure student progress in the attainment of the Core Curriculum Content Standards. Under the No Child Left Behind Act of 2001 (NCLB), all states are required to assess student progress in Language Arts and Math in Grades 3-8 and Grade 11. The state also assesses science in Grades 4 and 8. High schools show assessment results from the administration of the High School Proficiency Assessment (HSPA) in Language Arts and Math. The HSPA is the test that students must pass in order to graduate from high school. Retests are not included in these results. (NJDOE, 2011a)

Average Class Size. Average class size for secondary schools (9-12) is based on the total enrollment per grade divided by the total number of English classes for the same grade. For secondary grades, the state average is the total enrollment for each grade divided by the total number of English classes for the same grade (NJDOE, 2011a).

District Factor Group (DFG). The state of New Jersey uses the District Factor Group system for ranking the socioeconomic status of school districts. School districts in New Jersey are designated as "A-J" based upon socioeconomic factors identified in the U.S. Census data. "A" districts are those schools districts with the lowest socioeconomic status and "J" districts are those school districts with the wealthiest socioeconomic status. Factors such as adult education levels, poverty, unemployment rates, and median income are used to group districts with similar socioeconomic status. However, as of April 2013, NJ no longer uses DFG factors for comparison purposes. "DFGs placed districts, not schools, into eight groups based on the socioeconomic conditions of the communities they served. Instead of the DFGs, the DOE is using a methodology called “Propensity Score Matching,” which creates a list of “peers” for each school in New Jersey, grouping schools together based on shared demographic characteristics, namely student poverty, limited English proficiency, and Special Education classification” (Krengel, 2013).

Elementary and Secondary Education Act (ESEA). ESEA was passed in 1965 as a part of the "War on Poverty." It emphasizes equal access to education and establishes high standards and accountability. The law authorizes federally funded education programs that are administered by the states. In 2002, Congress amended ESEA and reauthorized it as the No Child Left Behind Act (NCLB).

Faculty Attendance Rate. This is the average daily attendance of the faculty of the school calculated by dividing the total number of days present by the total number of days contracted for all faculty members (NJDOE, 2011a).

Faculty and Administrator Credentials**.** These are percentages of faculty and administrative members in the school who hold a bachelor’s, master’s, or doctoral degree. For vocational and special services schools, there is also information about licenses or certification in addition to or in place of degrees (NJDOE, 2011a).

Faculty Mobility Rate. This represents the rate at which faculty members come and go during the school year. It is calculated by using the number of faculty who entered or left employment in the school after October 15 divided by the total number of faculty reported as of that same date. (NJDOE, 2011a).

Free or Reduced Lunch (Socioeconomic Status). Students are entitled to free lunches if their families’ income is below 130% of the annual income poverty level guideline established by the U.S. Department of Health and Human Services and updated annually by the Census

Bureau (currently $23,550 for a family of four). The poverty guidelines are issued each year in the *Federal Register* by the Department of Health and Human Services. The guidelines are a simplification of the poverty thresholds for use for administrative purposes (e.g., determining financial eligibility for certain federal programs). Children that are members of households receiving food stamp benefits or cash assistance through the Temporary Assistance for Needy Families block grant, as well as homeless, runaway, and migrant children, also qualify for free meals. Students with family incomes below 185% of the poverty level are eligible for a reduced price lunch. Schools cannot charge children who receive reduced price lunches more than 40 cents per meal, but each school food authority sets the exact student contribution level independently.

High-Poverty Schools. Defines public schools where 76% or more students are eligible for Free/Reduced Lunch (National Center for Education Statistics (NCES), 2012).

High School. For the purposes of this study high school refers to New Jersey comprehensive public schools with educational Grades 9, 10, 11, and 12.

High School Exit Exams**.** A test a student may be required to take in order to show proficiency in a major subject or as in the case with high school to exhibit basic proficiency in math and English to gain a high school diploma.

High-Stakes Exams. At the high school level, this is a test tied to graduation. A student is required to pass this type of exam in order to obtain a high school diploma. According to NCLB, all states must test high school students but the tests need not be “high-stakes” exit exams tied to graduation.

Instructional Time**.** This is the amount of time per day that a typical student is engaged in instructional activities under the supervision of a certified teacher. (NJDOE, 2011a).

Length of School Day. This is the amount of time a school is in session for a typical student on a normal school day (NJDOE, 2011a).

Length of School Year. This is the number of days in the regular school year. A school year that includes 180 teaching school days (NJDOE, 2011a).

Low-Poverty Schools. Defines public schools where 25% or fewer students are eligible for Free/Reduced Lunch (National Center for Education Statistics (NCES), 2012).

NJ High School Proficiency Assessment (HSPA). The NJ HSPA is used to determine student achievement in reading, writing, and mathematics as specified in the New Jersey Core Curriculum Content Standards. First-time 11th grade students are eligible to take the NJ HSPA exam in March of their junior year. It is a "high-stakes" exam. HSPA scores are reported as percent proficient in each of the content areas as part of the NJ School Report Card data; individual student scores are reported as scale scores. High schools show assessment results from the 11th grade spring 2011 administration of the High School Proficiency Assessment (HSPA) in Language Arts and Math. The HSPA is the test that students must pass in order to graduate from high school. Retests are not included in these results. (NJDOE, 2011a)

NJ School Report Card Data. The data presented in this report card will differ slightly from the data in the No Child Left Behind (NCLB*)* reports required by federal law. The NCLB reports show assessment results in three grade spans after the application of NCLB rules for the purpose of calculating adequate yearly progress (AYP) and identifying schools in need of improvement. By contrast, the assessment results presented in this report card have had no restrictions or conditions applied to them. These data are the state's assessment results that have been disaggregated into subgroups for all students who attend a school. (NJDOE, 2011a).

No Child Left Behind (NCLB). Congress passed the NCLB education reform policy in 2001 and President George W. Bush signed it into law on January 8, 2002. NCLB mandates that all states focus on improving student academic performance while bridging the achievement gap of all students. NCLB requires schools to test students and document their academic progress. States are required to meet the goal of 100% proficiency by the year 2014.

Proficiency Levels. Not all states require the same level of proficiency. In New Jersey proficiency level means the student scored no less than 200. Students must pass each section of the NJ HSPA test. The scores on each section of the test range from 100 to 300 and the passing score is 200.

School Percentage of Limited English Proficient (LEP) Student. This is the percentage of LEP students in the school. It is calculated by dividing the total number of students who are in Limited English Proficient programs by the total enrollment (NJDOE, 2011a).

Student Achievement. Student achievement for the purpose of this study happens when the student's scaled score falls in the Proficient or above (Advanced Proficient) range on the NJ HSPA test.

Student Attendance Rate. Refers to the grade-level percentages of students on average who are present at school each day calculated by dividing the sum of days present in each grade level by the sum of possible days for all students in each grade (NJDOE, 2011a).

Student Mobility Rate. This is the percentage of students who both entered and left during the school year. The calculation is derived from the sum of students entering and leaving after the October enrollment count divided by the total enrollment (NJDOE, 2011a).

School Percentage of Students with Disabilities. This shows the percentage of students with an Individualized Education Program (IEP), including speech, regardless of placement and programs. This is calculated by dividing the total number of students with IEPs by the total enrollment (NJDOE, 2011a).

School Size (Enrollment by Grade). The enrollment for this study was obtained from the school districts' NJ SMART state submission. NJ Standards Measurement and Resource for Teaching (NJ SMART), is a comprehensive data warehouse, a source of student level data reporting, and unique statewide student identification (SID) system (NJDOE, 2011a).

Student/Faculty Ratio. This is the number of students per faculty member. It is calculated by dividing the reported October school enrollment by the combined full-time equivalents (FTEs) of classroom teachers and educational support services personnel assigned to the school as of October of the school year (NJDOE, 2011a).

Student Suspensions. These are percentages of students who were suspended at least once during the school year. Students suspended more than one time are counted once. The percentages are calculated by dividing the total number suspended by the total enrollment (NJDOE, 2011a).

Organization of the Study

In Chapter I, the researcher established an overview of the problem and background information related to the length of the school day and student achievement.

Chapter II encompasses a review of literature pertaining to length of the school day and student achievement. It provides background information on other factors that influence student achievement and that are reported on the NJ School Report Card.

Chapter III, along with Chapter I, explains the design methods and procedures for this study. Data were collected from the Grade 11, 2011 NJ HSPA test results as reported on the NJ DOE website and part of the information contained on NJ School Report Cards.

In Chapter IV the researcher presents the data and the statistical findings from analysis.

Chapter V presents a statistical summary and data implications for administrative and education practices and policies. Conclusions drawn are based on the research question: What is the strength and direction of the relationship between length of school day on the Grade 11, 2011 New Jersey state-mandated High School Proficiency Assessment (HSPA scores) in Language Arts and Mathematics?

CHAPTER II

LITERATURE REVIEW

Introduction

My purpose for this study was to explain the strength and the direction of the relationships between the length of the school day and other school variables found in the extant literature that influence student achievement and the aggregate school NJ HSPA scores in Grade 11 Language Arts and Mathematics.

The main research question guided this literature review. Search terms used in the literature review included High-Stakes Testing, School Variables (including Length of the School Day, Socioeconomic Status/SES), Teacher Variables, and Student Variables as listed on the 2011 NJ School Report Card. This study reviewed the current and seminal literature on the relationship between length of the school day and student achievement scores on the NJ HSPA 2011 and further establishes a profile on the relationship between student, school, and teacher variables, and student achievement.

The objective of this review was to identify empirical studies that tried to ascertain a statistical significance, if any, related to student, school, and teacher variables on student achievement in Grade 11 as measured by the NJ HSPA tests in Language Arts and Mathematics. References cited by other researchers were explored to expand and uncover relevant information.

The Cardinal Principles of Secondary Education (1918), a seminal work, focused on the function, and structure of secondary education, emphasizing that “any well-planned high school curriculum should be accepted as a preparation for college” and that the responsibility of high schools should be to develop “young people to meet the needs of democracy” (p. 5). Profoundly visionary in its philosophy, *The Cardinal Principles* (1918) imbued the need for schools to undergo comprehensive reorganization from time to time and to develop the potential worth of each student (pp. 7, 32). *The Cardinal Principles* (1918) also invoked the notion that serious attention to secondary schools must be made, suggesting that analyzing methods, social needs, educational theory and practice should be studied by many, including administrators and teachers (p. 32).

The Eight-Year Study, another seminal work, acclaimed by Tanner & Tanner (2007) as "the most important and comprehensive curriculum experiment ever carried on in the United States" (p. 85), dealt with the relationship between school and college. Many of the issues surrounding the Eight-Year Study beleaguered the Commission in the 1930s and still ruminate today. What evolved in education as a result of the Eight-Year Study and the Cardinal Principles may not have changed college entrance criteria or the focus on college preparatory courses at the secondary school level, but what did result was a much richer awareness about the learning process and the impact that we can make to improve education at the school level through research and data.

Social forces today are more apparent than they were in the 1930s. Globalization, technological advances, communication patterns, energy consumption, and the competition for resources and jobs mandate changes in schools. The demand for educational results and choice has spurred controversial issues such as school vouchers and charter schools. The competition for scarce resources is keen. Federal, state, and local governments have become deeply entrenched in managing education and legislating reform in structure and accountability. Nevertheless, standards-based reform is not concerned with student needs or social theory. Either by accident or through a thoughtful plan, the Commission (in the Eight-Year Study) brought together all the stakeholders in a cooperative, problem-solving effort; in a similar way we must do so as well, as educational reform cries out to lengthen the school day or school year. Currently, all the forces wanting to make changes in schools are not necessarily working together. Failure will be high and steep if we do not produce meaningful change within our schools and classrooms that is based upon empirical research.

Literature Research Procedures

The literature reviewed for this chapter was accessed via online databases including EBSCO host, ProQuest, ERIC, JSTOR, and Academic Search Premier as well as online and print editions of peer-reviewed educational journals, dissertations, books, and reports. Unfortunately, during this review, the Education Resources Information Center better known as ERIC experienced a security breach; the breach was based on a discovery that personally identifiable information was released in some documents. At one point, ERIC, the world's largest digital library of education literature, became dysfunctional as a viable data source for document retrieval for this study.

Some of the keywords used to locate literature in the research included extended school time, school day, length of the school day, student achievement, academic achievement, socio economic status, high school testing, student mobility, faculty mobility, class size, teacher quality, achievement testing, accountability, and exit exams. Literature on the length of the school day and other variables connected to achievement generated relevant information for this study. Reviewing and using the bibliographies from scholarly works assisted in broadening the scope of evidence, a strategy that provided a greater number of valid resources and/or data about length of the school day, high stakes testing, and student achievement.

Experimental research in its truest sense was unavailable for the explored variables; therefore, a significant reliance on meta-analysis and quasi-experimental data became relevant.

Boote and Bielle (2005) offer a framework in their “literature review scoring rubric” (p. 8). Broadly, the rubric categories of “coverage, synthesis, methodology, significance, and rhetoric” (as explained in Boote and Bielle, 2005, p. 8) were used to analyze and compare research studies as part of this review.

Methodological Issues

In reviewing the literature, particularly the research related to the length of the school day and the variables linked to influencing student achievement, many shortcomings were uncovered: a lack of experimental studies placed a substantial emphasis on correlational designs; some studies did not report effect sizes; others had confusing mixed results using the same data; others were conducted in non-public school settings; most were single point in time studies; some were longitudinal studies but did not account for differences in the groups from year to year; others interchanged terminology; and finally terminology from study to study lacked consistency. A variety of studies reviewed included non-experimental and quasi-experimental research to provide a cross-section of available scholarly work. Johnson (2001) confirmed that most educational research is not experimental because it is impractical to design and conduct.

Both the federal and state governments are exerting greater influence over school funding; as such, governmental entities influence which variables get addressed in the debate on school variables and their relationship to student achievement. Determining which school, staff, and student variables statistically influence or have little significance on NJ HSPA Language Arts and Math scores was part of this study.

Several studies have explored and examined NJ Report Card variables and student achievement: Amato (2010), Cabezas (2006), Graziano (2012), Jones (2008), Gemellaro (2012), Michel (2004), and Tramaglini (2010), although none have focused on the length of the school day.

Very few studies have researched NJ Report Card individual variables and their effect on NJ HSPA scores. Jones (2008) analyzed 49 Report Card variables to assist in creating a predictive model for assessing a school's Average Yearly Progress (AYP) related to eleven NCLB subgroups and their associated scores on the NJ HSPA. The findings from Jones (2008) declared that eight or nine variables account for 90% of variability in passing the literacy and math sections of the NJ HSPA respectively (pp. 57, 58, 66). Jones (2008) focused on analyzing the intersection of expectations against the meeting of a school's AYP (p. 95). The school sample sizes in Jones' (2008) analysis appeared to be relatively small: n=282 for HSPA Language Arts and n=282 for Math (pp. 57, 66). The sample size in the Jones (2008) study did not meet the minimum requirements for simultaneous and hierarchal regression as defined by Field (2009 who cited Green, 1991): "He (Green) recommends a minimum sample size of 50 + 8*k*, where *k* is the number of predictors" (Field, 2009, p. 222). Therefore, Jones (2008) would have needed a sample size of 442 or larger (50 + 8 x 49 = 442) to meet the minimum sample size requirements to conduct the analysis. Additionally, Jones (2008) used SAT scores to determine the expected achievement on the NJ HSPA. Many of the same variables that affect SAT performance also affect HSPA performance and therefore including the SAT results as a variable in the Jones (2008) model might have had the potential to cause multicollinearity issues with the other predictor variables. Also, not all first time eleventh graders take the SAT exam and many of the ones that take it also go to tutoring sessions to bolster test scores. "It is known that test scores also reflect test-preparation, repeat test-taking and other 'test-wise' strategies aimed at boosting scores" (Geiser, Santelices, & University of California, 2007, p. 26). Additionally, because Tienken (2011) found conditional standard error of measure (CSEM) of about 10 points on the HSPA test and the correlation between the SAT scores and the HSPA scores might be problematic.

Graziano (2012) analyzed the influence of faculty mobility (a NJ Report Card staff variable) on NJ HSPA scores and found a weak but significant correlate to HSPA Math performance, $p=0.61$ (pp. 153, 162). Tramaglini (2010) studied K-12 districts (n=261) to reconfirm the relationship between school size and achievement at the district and high school levels. The analysis by Tramaglini (2010) sustained the validity of previous studies "indicating that a statistically significant negative relationship exists between high school enrollment size, district enrollment size, and student achievement" (p. 35). More specifically, Tramaglini (2010) found negative relationships between school district size and HSPA Mathematics "*-0.205*" as well as Language Arts at "*-0.190*" (p. 33). Furthermore, Tramaglini (2010) suggested that consolidating NJ schools and or regionalization could negatively impact high schools which are categorized in the lower socioeconomic status spectrum. "As high school enrollment size increases in New Jersey lower socioeconomic schools, student achievement in Language Arts and Mathematics on the HSPA appears to decrease" (Tramaglini, 2010, p. 34).

Since few studies center on the length of school day and its influence on student achievement at the high school level, the goal of this study was to provide evidence on how much variance, if any, the length of the school day (as a predictive variable) has on aggregate student performance on Grade 11 NJ HSPA scores.

Lengthening the school day or school year will necessitate the use of precious education resources. The results of my research intend to inform education leaders, researchers, and policymakers so that decisions about the length of the school day (as part of school reform) will be based on empirical evidence and not on rhetoric.

Inclusion and Exclusion Criteria for Literature Review

Studies that involved charter school populations and those that included pre-school, kindergarten, or lower elementary grades were excluded from this review because those grade levels are too divergent to draw appropriate, analogous conclusions to public high school student populations. Studies that involved the NJ Report Card variables and testing were included in the literature review. Current studies, peer reviewed articles, scholarly works, government reports, books, several dissertations, as well relevant or seminal work that could explain or provide background information or data on the dependent or independent variables and predictor variables were included in the literature review. Culling more recent research from 2005 to 2012 drove the significant selection of information included in this study. However, this literature review also used work found outside that date range because information on certain variables was unavailable or because it was deemed significant, such as seminal or pivotal research.

Each section of the reviewed literature includes empirical and data-based research:

- Experimental, quasi-experimental, meta-analysis, and/or non-experimental studies or those that could be considered causal-comparative**.**
- Peer-reviewed articles
- Peer-reviewed dissertations, government/policy reports
- Reports with statistical significance
- Scholarly books
- Seminal work
- Anecdotal and governmental data

- Any literature that met the above design criteria found in a report from a governmental agency

New Jersey School Report Card

The NJ Department of Education (NJDOE) publishes Report Cards for each public school annually. The NJ School Report Card data inform and report on educational progress by district for accountability purposes. Both the federal No Child Left Behind (NCLB) and state legislation require reporting by schools/districts to determine progress in meeting proficiency levels and how well a school is preparing students for college or career readiness. These reports offer information to the public about school performance as well as convey valuable data to educators and districts to assist in setting goals, developing local improvement plans, and making comparisons against peer schools. Most recently, the Department of Education established interventions in Priority Schools–those schools performing in the lowest 5% among all schools in the state during the past three years. State interventional support for these schools includes Regional Achievement Centers (RAC's). NJ Report cards include data on five major segments: (1) school environment, (2) student information, (3) school performance, (4) staff information, and (5) district financial data. The report cards display data in an easy to read layout with fewer complexities than other available formats.

Review of Literature Topics

Although Shea and Ceprano (2013) did not write about length of the school day, they capitalized on the impact of school legislation. “The advent of No Child Left Behind, with the high-stakes testing mania it generated, ushered in an era of methodology that ignores findings from decades of educational research” (p. 6.). For example, the data supported by the seminal work The Coleman Report of 1966 has been discounted for decades and still engenders a source of controversy. The Coleman Report sought to equalize education and to reduce the disparity between Black minorities and White students; it underscored the need to integrate schools not by race but by socioeconomic status. However, as a result of the Coleman Report, the installment of busing students out of their neighborhoods was introduced to education as a way to integrate and equalize schools; but busing was based on integration by race and therefore the reform failed. In addition, the Coleman Report got the public to realize that funding was not closely associated with achievement. Nevertheless, bureaucrats still accentuate that funding is a major solution to education equality.

High-Stakes Testing

"Achievement testing is a very complex enterprise, and as a result, test scores are widely misunderstood and misused" (Koretz, 2008, p. 1). Popham (2001) pointed out that high-stakes testing is "doing serious educational harm to children; because of the misuses in testing, instruction quality becomes eroded" (p. 1). Several researchers asserted the misguided goal of these tests includes measuring student success, instructional quality, effectiveness of educational programs, district rankings, and making school comparisons (Horn, 2004; Huebert, 1999; Popham, 2001; Solley, 2007).

Beginning with the 1965 Elementary and Secondary Education Act (ESEA), a dependence on standardized achievement tests formed a way to measure student achievement, and it became the norm. "U.S. educators must accept the blame for simply rolling over and allowing their teaching to be evaluated by students' scores on those off-the-shelf tests" (Popham, 2001, p. 10). "Tests now being used in high-stakes assessment programs are generally all wrong" Popham, 2001, p. 16).

Tanner & Tanner (2007) espoused Jefferson as “one of our most important educational philosophers” (p. 4). Why? Because Jefferson was the first to propose a system of public education and his beliefs about education: “to develop an intelligent citizenry and to provide educational opportunities that guarantee each individual the chance for optimal development” (Tanner & Tanner, 2007, p. 4). Standardized tests undermine this philosophy since those especially challenged drop out of school when they cannot pass high-stakes tests such as the NJ HSPA.

Ou (2009) claimed that his regression discontinuity analysis of the impact of failing the New Jersey high school exit exam indicated that “ . . . students who barely failed the exam were more likely to exit than those who barely passed, despite being offered retest opportunities” (p. 171). According to Ou (2009), because “high school exit exams are more prevalent in states with higher percentages of economically disadvantaged and minority students” many of those marginalized groups do not graduate (p. 171). Exacerbating this problem was the fact that “the difference in dropout probability among those who barely fail and those who barely pass is larger for racial-minority students, economically disadvantaged students, and for math tests relative to English tests” (Ou, 2009, p. 172).

Tyler (1966) first proposed the terms of assessment and educational achievement related to the appraisal of groups of people from different diverse groups. Koretz (2008, p. 37) spoke about student measurement: “standardized tests can measure a great deal that is of value.” This philosophy is also supported by E. F. Linquist, who, according to Koretz (2008), “did more to foster the development and use of standardized achievement tests” (p. 36). However, as quoted by Koretz (2008, p. 37), “Linquist and test manuals warn that achievement tests are incomplete and should not replace other information about student performance.” Tienken (2011) found a technical interpretation flaw he calls "conditional standard error of measurement (CSEM)" (p. 301) in the construct validity of high school exit exams/high-stakes tests. That translates into the fact that there is a margin of error on all these tests which can, for example, result in ±10 points from a student's individual true scale score. That means that many students may in fact pass the high-stakes test but be categorized as failing and therefore be prevented from graduating from high school. Popham (2001) heralded a slightly different but somewhat similar opinion about test scores: On any given day a student may score differently than if tested on the very next day.

> A child can take a national standardized achievement test on Monday, retake the same test on Tuesday, and come up with significantly different scores each time. Kids feel different on different days. The standardized tests used in education simply aren't as super-accurate as most folks think. (Popham, 2001, p. 32)

Furthermore, Tienken (2011) suggested that adjustment to policy should be made to ameliorate the impact of CSEM on a single test score that determines the fate of students and families.

> Because high school exit exams and CSEM are nationwide phenomena, perhaps hundreds of thousands of students might have been potentially negatively affected in the *NCLB* era by what appears as inaction at the state and national levels to develop policy remedies aligned with standards and recommendations for appropriate testing practices (Tienken, 2011, p. 310)

Historical View of High School Exit Exams

High-stakes high school exit tests became a universal policy tool in some states including New Jersey in the post No Child Left Behind (NCLB) era, and therefore researchers should seek to define the relationship of variables impacting test scores to encourage educational policy reforms based on science and not politics. Many states, including New Jersey, require high school students to pass an exit exam as a graduation requirement. According to Ou (2009), because “high school exit exams are more prevalent in states with higher percentages of economically disadvantaged and minority students,” many of those marginalized groups do not graduate (p. 171).

NCLB required greater accountability for schools to receive federal funds. High school exit exams were one way that states sought to improve the quality of secondary schools and to quantify student achievement. However, Ou (2009) countered that state exit exams provide “very little causal research on their benefits, including whether exit exams effectively raise students’ academic skills” (p. 171). According to McIntosh (2012), the “Obama Administration has made the adoption of college- and career-readiness standards and assessments a priority for competitive grants under the federal Race to the Top (RTTT) program and a condition for receiving waivers of No Child Left Behind (NCLB) requirements” (p. 23).

In 1975, the New Jersey Legislature passed the Public Schools Education Act (PSEA) to provide equal educational opportunity to all regardless of socioeconomic status, or geographic location. However, “the legal basis for the use of a test as a graduation requirement in the State of New Jersey” (NJDOE, 2006b, p. 1) was formulated as an amendment to the PSEA and signed into law in 1976. Ninth graders from 1981-1982 needed to pass a “Minimum Basic Skills Test (Reading and Mathematics)” (NJDOE, 2006b, p. 1) in order to receive a New Jersey high school diploma. A more challenging test was adopted in 1983 to test reading, mathematics, and writing and called the "Grade 9 High School Proficiency Test (HSPT9)" (NJDOE, 2006b, p. 1). In 1985-1986 the test became a graduation requirement. Then in 1988 a change was made to administer the test to Grade 11 students versus Grade 9. Further, from 1993-2001 New Jersey's high school exit exam was entitled Grade 11 High School Proficiency Test (HSPT11) and was subsequently replaced in 1996 by what is now known as the High School Proficiency Assessment (HSPA). Later in the spring of 2002 the HSPA developed into a graduation requirement (NJDOE, 2006b, p. 1).

New Jersey was one of the first states to enact a high school exit exam requirement. Many states have adopted High School exit exams since New Jersey and Florida first adopted this form of assessment in 1976. More interesting to note is that the adoption of high school exit exams has not been universal. As shown below, 25 states installed high school exit exams (with Rhode Island planning an exit exam in 2014 (McIntosh, 2012). State exit exams are random; not all states and their students are being assessed nor held accountable on equal terms (McIntosh, 2012; Warren & Kulick, 2007). Some reasons states do not implement exit exams are budgetary, while others indicate that colleges do not use the measure for entrance decisions, and still others prefer to use end-of-course exams as opposed to one comprehensive exam that tests multiple subjects. McIntosh (2012) emphasizes that "nearly 7 out of 10 students, and an even larger share of students of color, attend school in states with exit exams. Sixty-nine percent of the nation's students are enrolled in states with exit exams, including 71% of African American students, 85% of Hispanic students, 71% of low-income students, and 83% of English language learners (ELLs)" (p. 2). Since socioeconomic status and minority marginalized groups have been proven to be variables significantly influencing student achievement, it is perplexing that these disenfranchised groups are the very ones being tested and held accountable in order to receive a high school diploma; this screams of inequity and discriminatory practice. In the future, McIntosh (2012) indicated that high school exit exam replacement assessments (due to Common Core Standards, College-Career Readiness Standards, and the lack of current use by post-secondary institutions for entrance decisions) would most likely cause exit exams to become more rigorous. Several states have phased out or will phase out exit exam requirements and some will replace them with new assessments aligned to the common core standards; states phasing out or eliminating exam include North Carolina, Washington, Tennessee, Utah, Hawaii, Alabama, and Georgia.

Because New Jersey is not likely to eliminate the substantial force of high school exit exams as a graduation requirement, the actors who create education policy, school administrators, and the community still need to know the extent to which school and student independent variables influence the current HSPA exam because the independent variables will remain constant while the dependent variable (the exit exam) may change. On the horizon for New Jersey is the adoption of the Partnership for Assessment of Readiness for College and Careers (PARCC) exam slated to replace the NJHSPA and planned for the year 2014 (McIntosh, 2012, p. 31).

Holme (2010) warned, as cited in McIntosh (2012) that studies conducted by Grodsky et al. (2009) and Reardon et al. (2009) form strong conclusions that should prevent educators from assuming student achievement gains or losses emanate in any way from the mere implementation of high school exit exams. Furthermore, McIntosh (2012) contended that although results from empirical research says the opposite, “Proponents of exit exams, who often include state governors, chief state school officers, and state boards of education, maintain that requiring students to pass an exam will raise academic achievement and ensure that students graduate from high school with the knowledge and skills needed for college or careers" (p. 36). In fact, "the evidence indicates that low-achieving students—those often targeted by these policies—do not experience gains under the more rigorous exams" (McIntosh, pp. 487-488).

Table 2

States with High School Exit Exams as a Graduation Requirement

26 States Have or Will Implement High School Exit Exams as a Graduation Requirement					
State	Year Implemented	State	Year Implemented	State	Year Implemented
Alabama	1981	Massachusetts	1993	Oregon	2012
Alaska	1997	Maryland	1977	Rhode Island	2014
Arkansas		Minnesota	1992	South Carolina	1984
Arizona	1997	Mississippi	1982	Texas	1984
California	1999	New Jersey	1976	Virginia	1978
Florida	1976	Nevada	1977	Washington	1993
Georgia	1985	New Mexico	1986		
Idaho		New York	1977		
Indiana	1992	Ohio	1987		
Louisiana	1986	Oklahoma	2012		
Note. Adapted from "Modeling states' enactment of high school exit examination policies," by J. R. Warren & R. B. Kulick, 2007, *Social Forces*, *86*, p. 216; "State High School Exit Exams: A Policy in Transition," by S. McIntosh & N. Kober, 2012, *Center on Education Policy*, pp. 5, 8.					

In New Jersey, the High School Proficiency Assessment (HSPA) is an exit exam taken by all first-time Grade11 New Jersey students in public education. The NJDOE bureaucrats monitor high school student achievement via the NJ HSPA results for Annual Yearly Progress (AYP). If schools or districts fail to make AYP, the district officials and students suffer increasingly punitive measures with the final step being school closure or district takeover.

Student Variables

Student Attendance Rate

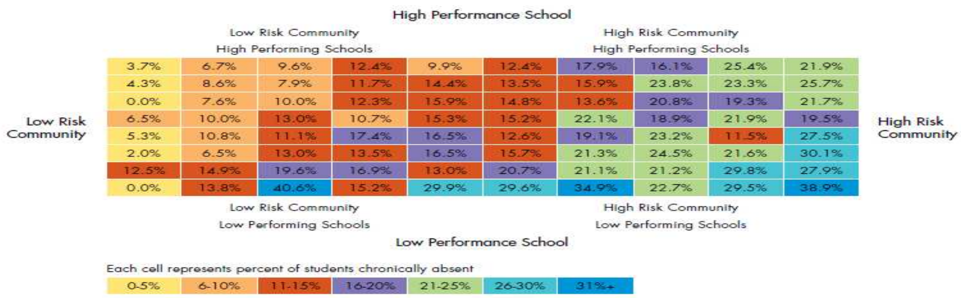
Student school attendance has been linked to achievement. Gottfried (2010) evaluated the relationship between student attendance and achievement in Philadelphia elementary and middle schools. What was found was a consistency in the results proving a "positive and statistically significant relationships between student attendance and academic achievement as expressed in GPA for both elementary and middle school students" (Gottfried, 2010, p. 434). "The effect sizes, as defined by the standardized regression coefficient, range from 0.24 to 0.34, thereby indicating that the attendance-achievement relationship is fairly consistent for the full sample and across elementary and middle school sample" (Gottfried, 2010, p. 446). Math achievement is especially sensitive to school absenteeism as well as standardized test scores and graduation and dropout rates (Balfanz & Byrnes, 2012, p. 3). Several researchers reported that students with healthier attendance histories have stronger test performance (Balfanz & Byrnes, 2006; Lamdin, 1996; Nichols, 2003). Roby (2003) concluded that based on the analysis of educational outcomes in Ohio for 3,171 schools (711 schools for 9th grade and 691 schools at 12th grade), a statistically significant relationship existed between attendance and achievement in 4th, 6th, 9th, and 12th grades.

> The correlation coefficient (Pearson's r) measured the strength or degree of the relationship between the two variables, student achievement, as measured by all tests passed averages on the Ohio Proficiency Tests, and student attendance, reflected in annual building attendance averages r = 0.57 (4th grade); 0.54 (6th grade); 0.78 (9th grade); and 0.55 (12th grade), (Roby 2003, p. 7).

Interestingly, not many state education departments report on the rate of student chronic attendance (missing 10% of the school year for any reason), which makes it difficult to track (Balfanz & Byrnes, 2012, p. 3). Furthermore, according to Balfanz & Byrnes (2012), that means that "a school can have average daily attendance of 90% and still have 40% of its students chronically absent, because on different days, different students make up that 90%" (p. 3). Constructively, New Jersey does report chronically absent students (those not present for 10% of the school year, for any reason) (NJDOE, 2011a). Children have to attend school in order to learn; chronic absenteeism for any child is detrimental for their on-going development but even more profound for younger children of poverty.

> During the early elementary years, children are gaining basic social and academic skills critical to ongoing academic success. Unless students attain these essential skills by third grade, they require extra help to catch up and are at grave risk for eventually dropping out of school (Chang, & Romero, 2008, p. 3).

Chang & Romero (2008) summarized and compared the significance of absenteeism on high-performing versus low-performing schools:



Note. From H. N. Chang & M. Romero, 2008, "Present, engaged, and accounted for: The critical importance of addressing chronic importance of addressing chronic absence in the early grades," by H. N. Chang & M. Romero, 2008, *Center for Children in Poverty*, p. 17. Copyright 2008 by Copyright Holder. Reprinted with permission.

Figure 1. Student Attendance Rates: High-Performing Schools in Low & High Risk Communities

> When chronic early absenteeism is relatively low (for example, between 0-8 percent), it is more likely to be related to economic and social challenges affecting the ability of individual families to ensure their children attend school regularly. When a large percentage of children are affected by chronic early absence (more than 20% of the population), it is likely indicative of systemic issues related to schools or communities (Chang & Romero, 2008, p. 17).

Students from low-income environments are particularly susceptible to chronic absenteeism. Chronic absenteeism increases beginning with middle school and continues until a student's high school senior year. Twelfth grade has the highest incidence of school absenteeism; accordingly, Morrissey, Hutchinson, and Winsler (2013) claimed that as a child ages and misses school, his or her grades tend to become more negative (p. 8). "Students who drop out of high school often have a history of absenteeism and grade retention" (Almeida, Johnson, & Steinberg, 2006; Lee & Burkam, 2000; Wise, 2008, as cited in Outhouse, 2012, p. 5).

Balfanz & Byrnes (2012) summarized the importance of chronic absenteeism:

> Because students reared in poverty benefit the most from being in school, one of the most effective strategies for providing pathways out of poverty is to do what it takes to get these students in school every day. This alone, even without improvements in the American education system will drive up achievement, high school graduation, and college attainment rates (p. 4).

The city of Chicago opened 23 smaller high schools from 2002-2007 to address absenteeism, low academic performance, and high dropout rates, particularly for at-risk students. The Chicago High School Redesign Initiative (CHSRI), reported by Sporte and de la Torre

(2010) was a combination of redesigned schools and new schools. CHSRI schools, whether redesigned or new, had insignificant outcomes; however; CHSRI did have some significant differences compared to similar students in non-CHSRI, or Chicago Public Schools (CPS), serving similar populations (Sporte & de la Torre, 2010 p. 15). “First time freshmen were recorded as having 10 less absences in CHSRI schools” (17.4 days) than other schools (27.8 days). According to Sporte and de la Torre (2010), CHSRI freshmen were more engaged and had better GPA’s in core subjects. The most outstanding positive effect reported in the Sporte and de la Torre (2010) study was the graduation rate: 49.9% for CHSRI students and 52.7% for CPS high school students (Sporte & de la Torre, 2010, p. 18). However, this initiative still failed to increase student test scores, and the authors speculated that the lack of test score growth might have been due to insignificant changes in instruction (Sporte & de la Torre, 2010, p. 24). My sense is that the lack of test score change is more than likely due to the socioeconomic status of the students.

Graziano (2012) described that student attendance was the strongest predictor of HSPA Language Arts (LA) and Math (MA) performance in every model run in the study analysis (p. 154). The results refuted Jones’ (2008) study, which stated that student attendance rate was not a significant predictor.

Little attention has been paid to student attendance at the public school elementary through high school levels. Empirical research focused on student attendance at the university level is now increasingly concentrated at public schools K-12. Recent studies have measured a causal impact of attendance on achievement on standardized reading and math test scores (Gottfried, 2010). The research denotes that student attendance is significant for student learning to occur, especially for students in low-income designated strata.

Student Suspension Rate

Michel (2004) incorporated suspensions as a student variable to be considered in analyzing NJDOE reported test scores. Coleman et al. (1966) first addressed the issue of disruptive behavior in schools and subsequent negative impact on learning. Flay, Allred, and Ordway (2001) implemented a comprehensive approach to character development in two separate school districts which "improved achievement by 15% to as much 52% and reduced disciplinary referrals by 78%-85%" (p. 71). "Self-concept is correlated negatively with several problem behaviors and academic performance" (Coleman et al., 1966; Filozof et al., 1998; Paulson et al., 1990; Purkey & Novak, 1984; Symons et al., 1997, as cited in Flay et al., 2001, p. 73).

Using PISA 2003 data, school disciplinary climate was found by Shin, Lee, and Kim (2009) to be a significant predictor on student mathematics achievement in three countries: Korea, Japan, and the United States. The sample sizes were Korea (n= 5425), Japan (n=4669) and the United States (n = 5292) (p. 520, 526). School variance, which included student-teacher relations and school disciplinary climate "accounted for 42% of the total variance in Korea, 54% in Japan and 26% in the United States (Shin et al., 2009, p. 527). "In schools where the disciplinary climate is strong, students tend to perform better both behaviourally and academically" (Kim et al., 2004; OECD, 2004; Purkey & Smith, 1983, as cited in Shin et al., 2009, p. 522). Furthermore, Shin et al. (2009) confirmed by citing Raudenbush and Bryk (2002) that "school differences in mathematics scores could be examined reliably with the school-level predictors" (p. 527). The differences in mathematics scores can be dramatically impacted by school climate and the classroom behavior of students.

Losen and Martinez (2013) estimated that over 2 million students (one out of every nine secondary school students) was suspended at least once during 2009-2010, the number being the highest nationally for Black males (p. 1). Unconscionably, the report indicated alarming rates of high school students (especially students of color) were suspended for minor infractions (Losen et al., 2013, p. 20). Naturally, suspended students are not in class learning. Barton, Coley, and Wenglinsky (1998) linked discipline offenses to "negatively impact academic achievement in mathematics, reading, science, and social science" (p. 3). The regression coefficients reported ranged from -.034 to .111 (some variables affected achievement more than others). More importantly, the r^2 reported for achievement levels was mathematics .070, reading .028, social science .027, and science at .069 (Barton et al., 1998, p. 49). Barton et al. (1998) began by surveying a nationally representative student group of 25,000 from 1988-1992; the final analysis could include only a sample size of 13,624 students because in order to be part of the analysis, students needed to participate in all three surveys years (eighth, tenth, and twelfth grades). Achievement was measured in student growth. These researchers found "disciplinary policies are associated with student delinquent behavior, which itself is associated with academic achievement" (p. 16). Therefore, the researchers concluded that "without order in our classrooms teachers can't teach and students can't learn" (Barton et al., 1998, p. 46).

Student Mobility Rate

Specifically, the NJDOE defines **s**tudent mobility as the number of schools a student enters and leaves during the school year. Student mobility has been linked to achievement. According to *Education*'s national survey data, the students who change schools the most frequently (four or more times) represented about 13% of all kindergarten through eighth grade

(K-8) students and they were disproportionately poor, African American, and from families that did not own their home" (Ashby, 2010, p. ii).

Students in the following categories exhibited the highest mobility rates: minorities, low-income, inner city, single parent, migrant, stepfamilies, and limited English proficiency (LEP) students (Ashby, 2010; Astone & McLanahan, 1994; Rumberger, 2003). The explanation for student mobility runs the gamut from complex financial pressures (unable to pay rent/utilities, seeking affordable, safe housing or employment); family instability (job loss, seasonal work, divorce, custody arrangements); student discipline problems; or a more positive, but less frequent reason: parents pursuing better educational circumstances. Mobility has also been correlated to result in negative academic achievement caused by two major factors: socioeconomically disadvantaged status and the lack of parental education (Ashby, 2010).

Highly mobile students exhibited low reading and math scores; many received special education services and were predicted to most likely repeat a grade (Ashby, 2010; Xu, Hannaway, & D'Souza, 2009). Consistent research findings indicated that reactive, frequent student moves negatively impacted academic success by about 1.5 percentage of a standard deviation (Hartman, 2002; Kerbow, 1966; Mehana & Reynolds 1995; Rumberger & Larson, 1998, as cited in Xu et al., 2009, p. 5). Aggregated moves (five or more) for non-promotional school changes caused a student to lose "7.7 percent of a standard deviation in math learning" (Xu, et al., 2009, p. 26)

Xu et al. (2009) conducted a six-year longitudinal study from 1997 through 2005 in North Carolina with four elementary Grade 3 level cohorts and found the following:

> School change reduces the expected score gains that a student would have achieved had the student not moved by about one and a half percentage of a standard deviation (one

> standard deviation of math score gains is about .5). The effect is small but significant. School mobility on average has no effect on academic performance of White students, but harms Black students (by about .025 standard deviations) and Hispanic students (by about .052 standard deviations). The loss in math achievement gains associated with student school mobility is three times as large for Special education students as that for non-Special education students. Low-income students also suffer academically from such moves while non-poor students on average experience no effect (p. 23).

Gasper, DeLuca, and Estacion (2012) provided high school mobility statistics garnered from the U.S. Bureau of Labor Statistics data contained in the National Longitudinal Survey of Youth 1997 (NLSY97): "71.9 % attended one high school, 19.8%, or 1:5, attended two high schools, 6.6% attended three high schools, and very few attended more than three high schools" (p. 502). Gasper et al. (2012) underscored that student mobility "is believed to put youth at risk for dropping out of high school." They cite other researchers to support this stance (Astone & McLanahan, 1994; Haveman, Wolfe, & Spaulding, 1991; Rumberger, 1995; Rumberger & Larson, 1998; South, Haynie, & Bose, 2007; Swanson & Schneider, 1999; Teachman, Paasch, & Carver, 1996, as cited in Gasper et al., 2012, p. 488).

High school students who changed schools versus those that attended one school exhibited the following characteristics:

> Switchers are less attached to their father figures, subject to less monitoring by their mother and father figures, and their parents are less likely to volunteer at school. Consistent with prior studies on the causes of switching schools, switchers also have lower academic achievement and higher disengagement than stayers. For example, youth who switch high schools are more frequently absent from school, have lower eighth-

grade GPAs, and are more likely to have been suspended from school than stayers (Gasper et al., 2012, p. 503).

Dropout rates for “school changers” were noted at 14.6 percentage points higher than those who stayed in school (Gasper et al., 2012, p. 509). The Gasper et al. (2012) study showed that dropping out of high school is not uncommon and that “about 12% of youth have not obtained a high school diploma by their early twenties” (Gasper et al., 2012, p. 512).

The value of a high school diploma in today’s society is greater than ever. Our nation’s youth who do not attain this credential find themselves unable to succeed in the competitive U.S. labor market. The skills they lack to obtain employment and succeed in society plague their lives; they may find themselves exposed to imprisonment, poor heath, and having children who are also at risk of dropping out of high school.

The research stated that “thirteen percent of students change school four or more times between kindergarten and Grade 8” (Kober, 2012, p. 11). Less than 30% of students switched high schools. Disengagement in school and increased dropout rates reported as high as 6% to 9% related to switching schools (Gasper et al., p. 512). The per student dropout cost was estimated at about $260,000 to the nation (Rouse, 2005, as cited in Gasper et al., 2012, p. 488).

Researchers showed that student mobility does account for decreased academic performance and increased student dropout rates.

Socioeconomic Status (Percentage of Students Eligible for Free or Reduced Lunch)

In this study, the NJ DOE Report card data for Grade 11 HSPA scores in 2011 reported SES in terms of free and reduced lunch; New Jersey has used that factor to compare student, school, and district socioeconomic status.

Congress commissioned a survey on educational opportunity through the National Center of Education Statistics of the U.S. Office of Education that resulted in the seminal work, *Equality of Educational Opportunity* (1966) by Coleman, Campbell, Hobson, McPartland, Mood, Weinfield, and York, better known as The Coleman Report; it was issued in response to section 402 of the Civil Rights Act of 1964. Coleman et al. (1966), among others, acted as research consultants with the major responsibility for survey design, administration, and analysis. The collection of data culled from 640,000 superintendents, principals, teachers, and students in a questionnaire focused on four major areas to find out: (1) the degree of racial and ethnic group segregation, (2) if schools offered equal educational opportunities using quality indicators, (3) the amount students learned by using achievement scores on standardized tests, and (4) achievement and the relationships between students as well as examining the types of schools attended (Coleman, et al., 1966, p. iii, iv). Coleman et al. (1966) found that most public schools were segregated and remained unequal but most importantly that schools have little effect on student achievement. Researchers Michel (2004), Pereira (2011), and Graziano (2012) all cited the findings of Coleman et al. (1966) against the backdrop of socioeconomic status by reporting the following:

> Socioeconomic status explained a greater proportion of student test scores than other measures of school resources such as class size and teacher characteristics; 49% student background, approximately, 42% teacher quality and 8% class size. The report showed that a school's average student characteristics, such as poverty and attitudes toward school, often had a greater impact on student achievement than teacher and schools and that the average teacher characteristics at a school had a small impact on a school's mean achievement (Graziano, 2012, p. 54; Michel, 2004, p. 29; Pereira, 2011, p. 53).

Kiviat (2000) also succinctly summed up the noteworthy findings of the Coleman report:

> disadvantaged Black children learn better in well-integrated classrooms . . . academic achievement was less related to the quality of a student's school, and more related to the social composition of the school, the student's sense of control of his environment and future, the verbal skills of teachers, and the student's family background (p. 114).

Coleman et al. (1966) dispelled the notion that school funding greatly affects student achievement. Instead, his findings suggested that socioeconomic status had the greatest impact on student achievement and that schools have little influence. His results (one of the most commonly cited works in education sociology) highlighted that student peers have the most significant influence on the educational achievement of other students. Coleman et al. (1966) underscored that children from strong family educational backgrounds can have a positive influence on low-income students but that low-income students do not have a negative effect on students from strong educational backgrounds.

Many other researchers, including Lytton & Pyryt (1998, as cited in Rogers et al., 2006), heralded socioeconomic status as the "most ubiquitous and significant influence on achievement found in almost all investigations of student achievement; they found that SES accounted for 35 to 50% of the variability in elementary school student achievement" (p. 732). Abrams & Kong (2012), Graziano (2012), and Tienken (2012) supported and conveyed the fact that SES is directly related to student achievement. Researchers studying student mobility also established that SES has a greater influence on Math than on LAL performance (Ashby, 2010; Xu, Hannaway, & D'Souza. 2009). Tienken (2012) advised that disadvantaged students have never been reported as scoring higher than their middle class or more advantaged peers on any state test at any grade level. The achievement differences between economically disadvantaged and economically advantaged students ranged from 12 to 36 percentile points on state-mandated high school tests of language arts and mathematics (Tienken, 2012).

What makes a difference in student achievement: “Family background characteristics and other out-of-school factors clearly have a profound influence on students' academic achievement” (Abrams & Kong, 2012; Colman, 1988; Sirin, 2005; West, 2012, p. 38) In fact, Coleman et al. (1966) first espoused that minority children (with weak family educational backgrounds) are likely to have increases in achievement when they are schooled with students with strong family educational backgrounds (p. 22).

Abrams and Kong (2012) most recently conducted a review of the research literature on variables closely associated with academic achievement. They ascertained that “research demonstrates that socioeconomic status (SES) is the strongest predictor of academic achievement” (Abrams & Kong, 2012, p. 1, 18). Abrams and Kong (2012) are supported in this finding by other researchers: Armor, 1995; Bradley, 2002; Caldas, 1993; Coleman et al., 1966; Duncan, 1994, 1995; Fetler, 1989; Gamoran and Long. 2006; Goldhaber, 2002; Hattie, 2009; Jencks et al, 1972; Lacour, 2011; Levanthal, 2000; Sirin, 2005; and White, 1982.

Although Abrams and Kong (2012) stated that SES in terms of family measures (parent income, parent occupation, and parent educational level) is the strongest predictor of academic achievement, they also found that school SES was also a strong predictor (pp. 2, 10). In sum, they found the variables most closely associated with student academic achievement were socioeconomic status (SES), parent education, family structure, school SES, ELL, and neighborhood SES.

Additionally, Abrams and Kong (2012) cited the researcher Keiffer (2008), who found that limited English proficiency is moderately associated with academic achievement (p. 14), but they could not validate this variable as a predictor of achievement. Student mobility, also reported in Abrams and Kong (2012), can be significant when the measure is associated with the number of school moves a student makes (p. 16).

Broadly, a conundrum posed by the OECD (2011) challenges researchers and policy-makers to look more closely at socioeconomic status for achievement and beyond that variable for answers by stating that “in the United States two students from different socioeconomic backgrounds vary much more in their learning outcomes than is typically the case in OECD countries” (p. 230). Furthermore, the OECD (2010b) iterated that the following:

> The comparatively close dependency of the learning outcomes of students in the United States on socioeconomic background is therefore not explained by a socioeconomically more heterogeneous student population or society, but mainly because socioeconomic disadvantage leads more directly to poor educational performance in the United States than is the case in many other countries” (p. 230).

OECD (2010b, 2011) espoused that “17% of the variation in student performance in the United States is explained by students’ socioeconomic background” (pp. 230, 232). Since culture can influence student achievement, the OECD (2011) also shared that “countries that place a high value on education get better educational results than countries that do not. The extent to which educational aspirations of parents are the result of cultural values or determinants of these and how such educational aspirations interact with educational policies and practices is an important subject that deserves further study” (p. 230).

Sirin (2005) affirmed that “Of all the factors examined in the meta-analytic literature, family SES at the student level is one of the strongest correlates of academic performance” (p. 438).

Reardon (2013) examined the U.S. achievement gap over the last 50 years and found it widening between high and low income families. The gap disparity started for those born during the 1970's; then in the year 2000 (which was about 20-25 years later) "the gap in standardized test scores was roughly 1.25 standard deviations—40% larger than the gap several decades earlier" (Reardon, 2013, p. 11). Although the black/white achievement gap has been reduced, it remains high. According to Reardon's (2013) study, "Economic inequality now exceeds racial inequality in education outcomes" (p. 12). In the last few decades, the college-completion rate among children from high-income families has grown immensely compared to the stagnant college completion rate among low-income families. Education has become increasingly important to economic success because low skilled jobs in manufacturing, for example, declined within the United States and have been replaced by high-skilled jobs within the information sector (i.e., systems architects, software engineers, financial analysts). Furthermore, the gap widened because of "the extent to which families invest their time and money in their children's education. Indeed, high-income families now spend nearly seven times as much on their children's development as low-income families, up from a ratio of four times as much in 1972" (Kornrich & Furstenberg, 2013, as cited in Reardon, 2013, p. 14). This supports the explanation for many differences in standardized test scores between two groups.

> It is unrealistic, however, to think that school-based strategies alone will eliminate today's stark disparities in academic success. Economic policies that reduce inequality; family support policies that ensure children grow up in stable, secure homes and neighborhoods; and early-childhood education policies that promote cognitive and social development should all be part of a comprehensive strategy to close the economic achievement gap (Reardon, 2013, p. 15).

Controversially, Harwell and LeBeau (2010) examined the national free and reduced lunch program and determined that the eligibility for free and reduced lunch (FRL) is a poor measure of socioeconomic status.

> In education research using the FRL variable, it appears that typically no distinction is drawn between students certified as eligible for a reduced price lunch (1.59 million) and those certified as eligible for a free lunch (16.1 million; NSLP, 2008) (Harwell and LeBeau, 2010, p. 121).

Percentage of Students with Limited English Proficiency

"All limited English proficient (LEP) students must take each content area of the HSPA. LEP students are provided accommodations and modifications during testing, which can include a translation dictionary, translation of the test directions, extended testing time, or a small group testing environment" (NJDOE 2006a, p. 2).

Statistically, LEP students are the fastest growing population nationally; LEP status is frequently associated with poor academic and behavioral results. "Estimates indicate that approximately 10.9 million school-age children speak a language other than English at home; and by the year 2030, it is estimated that approximately 40% of the school-age population will speak English as a second language" (Dowdy, Dever, DiStefano, & Chin (2011, p. 15). "It is generally known that the ELL population is at risk of dropping out; however, there is no direct statistical data available on the dropout rate in the ELL population" (Sheng, Sheng, & Anderson, 2011, p. 99). The reasoning behind this is that English proficiency directly relates to academic performance and grade retention.

Abedi (2004) postulated that adequate yearly progress (AYP) reporting of disaggregated; LEP student data exist in order to comply with NCLB. "Inconsistent LEP classification, as well as the sparse population of LEP students in many states, threatens the validity of adequate yearly progress reporting" (Abedi, 2004, p. 4). Graziano (2012) and Abedi & Dietel (2004) claimed that the LEP students achieved proficiency scores 20-30 points lower than non-LEP students had and that the alpha coefficients among LEP students differed considerably across the content areas.

> In math, where language factors might not have much influence on performance, the coefficient for LEP students (.802) was slightly lower than the coefficient for English-only students (.898). In language, science, and social science, however, the alpha coefficient gap between English-only and LEP students was large. Averaging over language, science, and social science results, the alpha coefficient for English-only students was .808, as compared with an average coefficient of .603 for LEP students. (Abedi, 2004, p. 8).

The upward growth trend of LEP student populations leaves insufficient time for these students to develop the level of English proficiency needed for valid testing, particularly in content areas needing greater academic vocabulary skill. "Thus, schools with larger numbers of LEP students are more likely to be cited as being "in need of improvement" than schools with fewer or no LEP students" (Abedi, 2004, p. 7).

The research conducted by Jones (2008) included running a regression analysis for the subgroup Limited English Proficiency (n = 269). A significant finding correlating the variable of Limited English Proficiency scores to the mathematics section of the HSPA indicated that more than 30% of the variability in passing the HSPA is explained by one variable, the Mathematical Scholastic Aptitude Test (SAT) exam score $R^2 = 0.301$, $F(1,60) = 25.831$, $p<.001$ (Jones, 2008, p. 73).

NCLB and education accountability was structured upon the state of Texas' already flawed educational system (Haney, 2000; Reyes, 2008; Watt, Powell, Mendiola, & Cossio, 2006; White, n.d., as cited in Giambo, 2010, p. 51). Many state high school exit exams aggregate scores of students who are no longer categorized or receiving specialized classes as an LEP with current LEP students; and according to Giambo (2010), this results in confusing public information or interpretation. High school exit exams require academic English proficiency and that makes it difficult for LEP students to be tested in content knowledge. When LEP students fail the test several times or are unsuccessful in alternative routes to a diploma, they get discouraged and drop out of high school. However, Giambo (2010) relayed that LEP students are encouraged to pursue a GED, but they are not counted in the reported dropout rates. "More research is needed in this area that will add to a clearer picture of the meaning of current policies for individuals and groups of students with limited English proficiency" (Giambo, 2010, p. 53)

Percentage of Students with Disabilities

"It is obvious that the use of exit exams for high school graduation is likely to increase, despite high failure rates among students with disabilities" (Yell, Katsiyannis, Collins, & Losinski, 2012, p. 63). For many students with disabilities, accommodations to standard testing are necessary to accurately measure the performance of these students (Lai & Berkeley, 2012, p. 160). Nevertheless, "IEP team members need to be aware that for some students, accommodations may not be beneficial or could even hinder performance, making a student's results less valid" (Lai & Berkeley, 2012, p. 168).

This subgroup as defined by the NJDOE (2011a) is the percentage of students with an Individualized Education Program (IEP), including speech, regardless of placement and programs. In accordance with the Individuals with Disabilities Act (IDEA), students who are receiving special education services must participate in the statewide assessment system, the High School Proficiency Assessment (HSPA). The New Jersey statewide assessments are designed to measure how well all students achieve the Core Curriculum Content Standards. Special education students must take the statewide assessment unless their individualized education program (IEP) specifically exempts them from taking one or more sections of the assessment. Special education students requiring accommodations or modifications should be tested using the modified testing procedures specified in their IEP and approved by the Office of Evaluation and Assessment. The accommodations or modifications should be the same as those used by these students in other classroom testing and may include Braille, extended testing time, or a different testing site (NJDOE, 2006a, p. 1).

The Individuals with Disabilities Education Act (IDEA), enacted in 1975, mandated that children and youth ages 3–21 with disabilities have the right to be provided with a free and appropriate public school education. The percentage of total public school enrollment that represents children served by federally supported special education programs increased from 8.3% to 13.8% between 1976–1977 and 2004–2005. Much of this overall increase can be attributed to a rise in the percentage of students identified as having specific learning disabilities (LD) from 1976–77 (1.8 percent) to 2004–05 (5.7 percent). The overall percentage of students being served in programs for those with disabilities decreased between 2004–05 (13.8%) and 2009–2010 (13.1%), (NCES, 2012). Progress has been made over time among this student subgroup:

> Graduation rates with a standard diploma for students with disabilities age 14 and older have increased from 52.6% in 1995–1996 to 56.2% in 1999–2000. In addition, the dropout rates decreased from 34.1% to 29.4% during the same time

> period (U.S. Department of Education, 2005, as cited in Katsiyannis, Zhang, Ryan, & Jones, 2007, p.166).

Unfortunately, Ysseldyke, Nelson, Christenson, Johnson, Dennison, Triezenberg, Sharpe, and Hawes (2004) did not find empirical evidence to confirm the negative or positive consequences of student performance on tests, especially students with disabilities; and this was confirmed by Katsiyannis, et al. (2007, p. 165). "Research is still needed to study the impact of large-scale assessment practices on special education instructional practices" (Ysseldyke et al., 2004, p. 84). There is a lack of consistent and systematic data collection on the "participation, performance, graduation rates, retention/ promotion, increased/decreased referral, and improved satisfaction for students with disabilities" related to high-stakes testing (Ysseldyke et al., 2004, p. 90). However, Ysseldyke et al. (2004) confirmed two facts related to students with disabilities and testing: "At least two matters interfere with test performance: (a) lack of opportunity to learn the content of the test, and (b) provision of those accommodations necessary to ensure access to the test" (p. 83). There are no assurances the accommodations during testing are being made or being made consistently.

> Findings showed that there continues to be large variability among states regarding allowed testing accommodations and that although there has been an increase in research conducted related to the effectiveness of accommodations for students with LD in the past decade, empirical evidence remains sparse and findings are often inconclusive (Lai & Berkeley, 2012, p. 158).

Most importantly, "de facto tracks that students are placed into once they fail a high-stakes exam are of most concern" Ysseldyke et al., 2004, p. 85). "The push for relevance to instruction, alignment with state standards, and the legal requirement for participation of students with disabilities in assessments are leading to changes in test development" (Ysseldyke et al., 2004, p. 84). Finally, Katsiyannis et al. (2007) warn that "it is likely that parents and advocates of students with special needs will continue to call upon the courts to ultimately determine what high-stakes testing is considered fair" (p. 166).

Jones (2008) analyzed the subgroup Students with Disabilities (n =269)—those who took and passed the literacy arts section of the NJ HSPA. Four of the 49 New Jersey Report Card factors (DFG, average score on verbal section of SAT, percentage of budget for teacher salaries/benefits, and percent of graduates at four-year colleges/universities) were significant; "75% of the variability in the passing rate of the literacy arts section of the NJ HSPA can be explained by the four variables: $R^2 = 0.745$, $F(1,264) = 2193.092$, $p<.001$" (p. 60).

Staff Variables

Faculty Attendance Rate

> On any given school day, up to 40% of teachers in New Jersey's Camden City Public Schools are absent from their classrooms. Such a high figure probably would not stand out in parts of the developing world, but it contrasts sharply with the 3% national rate of absence for full-time wage and salaried American workers, and the 5.3% rate of absence for American teachers overall (Miller, 2012, p. 1).

This statistic is further enlightened by other researchers who document that the absence rate for public school teachers in the United States is 5% to 6% of the days schools are in session (Ballou, 1996; Podgursky, 2003 as cited in Miller, Murnane, &Willet, 2008, p. 182).

One of the latest research findings from Miller (2012) includes the following:

> On average, 36% of teachers nationally were absent more than 10 days during the 2009-10 school year based on the 56,837 schools analyzed in the dataset. The percentages

reported by individual schools range from 0% to 100%, with 62% of the variation in the measure occurring between districts and a third occurring within districts (p. 2).

Stark differences surfaced when U.S. teacher absences were compared to other countries or to managerial and professional employee jobs. For example, in developing countries teacher absence rates reached 19% (Chaudhury, Hammer, Kremer, Muralidharan, & Rogers, 2006, p. 95), while industrialized nations such as the United Kingdom or Australia reported teacher absence rates at 3% (Bowers, 2001, p. 143; Bradley, Green, & Leeves, 2007); and finally teacher absence rates tended to be three times higher than corporate managerial and professional occupations (Ballou, 1996; Podgursky, 2003, as cited in Miller et al., 2008, pp. 182, 183).

Scant research literature examining the causal effects of teacher absences exists. Nevertheless, current research reinforces the fact that teachers contribute toward successful student achievement and that low faculty attendance rates negatively impact achievement.

Education resources are scarce, and the nationwide four billion dollars currently being spent on teacher absences could be better utilized in ways that ameliorate student achievement (Miller, 2012). Miller et al. (2008) estimated the impact of teacher attendance: "10 additional days of teacher absence reduce mathematics achievement of fourth-grade students by 3.2% of a standard deviation" (p. 181). These researchers explained that teacher absences make a difference in teacher effectiveness, although their results were limited to 200 teachers in one northeastern suburban school with a population of 4,000 students living in poverty. Clotfelter, Ladd, and Vigdor's (2007) broader longitudinal study in North Carolina used a larger data set. Clotfelter et al. (2007) "were able to control for time-invariant skill and effort levels of teachers and provided causal evidence that teacher absences negatively affect student achievement" (Miller et al., 2008, p. 184). "Evidence indicates that 10 additional days of teacher absences decreased student achievement by 1% or 2% of a standard deviation; this finding, however, speaks to the average effect across rural, suburban, and urban districts alike" (Miller et al., 2008, p. 184).

Interestingly, teachers at the elementary school level are absent more often than high school teachers (Bridges & Hallinan, 1978; Educational Research Service, 1980). Generally, females were reported as having higher absence rates than males; therefore, the difference in absences between elementary and high school teachers may be attributed to the demographical components: younger children are considered to be carriers of communicable diseases and female teachers are represented at the elementary level in greater numbers (Educational Research Service, 1980).

Some of the negative effects of teacher absences on students result in a lack of continuity and intensity of instruction, interrupted class routines, and a substitute's inability to differentiate instruction because student skill knowledge is not apparent or known (Miller et al., 2008). Miller et al. (2008, p. 183) cited other researchers who have found negative relationships between teacher absences and student achievement: Bayard, 2003; Beavers, 1981; Boswell, 1993; Cantrell, 2003; Lewis, 1981, 1991; Manatt, 1987; Pitkoff, 1989; Smith, 1984; Summers & Raivetz, 1982; Womble, 2001; and Woods, 1990.

Other findings by Miller et al. (2008) featured data to support the following reasoning:

> Tenured teachers are more likely to be absent than non-tenured teachers; male teachers are absent between one and two fewer days than are female teachers, holding all else equal (*p* < .01 for each specification; and African American teachers are consistently absent about three days more often than White teachers, on average, holding all else equal (*p* < .01 for each specification)" (p. 193).

Teachers commuting longer distances are more frequently absent (Miller, 2012). More importantly, "Students in schools serving predominantly low-income families tend to endure teacher absence at a higher rate than students in more affluent communities. Thus, it's plausible that achievement gaps can be attributed, in part, to a teacher attendance gap" (Miller, 2012, p. 5).

Future research suggested by Miller et al. (2008) would be "to examine the extent to which the impact of teacher absences on student achievement takes place through the mechanism of increasing student absences" (p. 197).

Faculty Mobility Rate

The faculty mobility rate represents how often faculty come and go during the school year. It is calculated by dividing the number of faculty who entered or left employment after October 15 of the school year by the sum of faculty on the same day. The implications of faculty mobility on the flow of the school year, teacher-student relations, and curriculum delivery have been documented. The students of teachers with lower turnover rates have higher test score gains (The Alliance for Excellent Education, 2008). Unfortunately, the mobility of faculty is much higher in economically low-income, poorer schools (Alliance for Excellent Education, 2008; Allensworth, Ponisciak, & Mazzeo, 2009; Planty, Hussar, William, & Synder, 2008).

Faculty mobility and teacher persistence have been terms found in the literature that are used interchangeably. However, teacher persistence typically denotes teachers leaving the profession, not merely switching assignments. Therefore, although related terms, the two have slightly different implications and uses in the literature. The teacher persistence variable is most often used in studies showing a relationship between teacher attrition and school environment (Goldhaber, Gross, & Player, 2011).

For two decades, the National Center for Education Statistics (NCES) has been recording teacher mobility information. Typically, attrition occurred most often after the first three years of teaching (Kaiser, 2011). Teacher mobility for 2007 and 2008 for beginning teachers in public schools was 10%, and these same teachers were not teaching at all in 2008-2009; in 2009-2010, 12% were not teaching. Another 10% were teaching in a different school in 2009-2010 other than the previous school year. During the year 2003-2004 the turnover rate for teachers in the United States was 21% for high-poverty districts (75% of students eligible for free lunch) versus 14% for low-poverty schools, where 15% or less of the student population was eligible for free lunch (Planty, Hussar, William, & Synder, 2008). A statistical analysis of new teachers in Georgia found that educators were much more likely to exit schools with large proportions of minority students (Scafidi, Sjoquist, & Stinebrickner, 2007).

Graziano (2012) analyzed faculty mobility rate as a predictor of student performance on the NJHSPA. The results of her analysis state that "faculty mobility is not a statistically significant predictor for HSPA LA performance when controlling for all school and student mutable variables (F change = 3.530; df = 1, 328; p = .061)" (p. 134). However, Graziano's (2012) study proved that faculty mobility and a faculty master's degree (MA) were statistically significant in relationship to HSPA Math performance "(F change = 6,968; df = 2,326; p <.001)" (p. 140).

Staff with Master's Degree or Higher

A spotlight on teacher quality was embodied in some of the latest legislation in New Jersey through the introduction of measuring and evaluating a teacher through student growth achievement (SGO). Coleman et al. (1966) surveyed teacher quality and found that the verbal acumen score and educational background of a teacher had the highest correlation to student achievement, chiefly for minority children (p. 22).

> One must also be aware of the relative importance of a certain kind of thing to a certain kind of person. Just as a loaf of bread means more to a starving man than to a sated one, so one very fine textbook, or better, one very able teacher may mean far more to a deprived child than to one who already has several of both (Coleman et al., 1966, p. 8).

Since Coleman et al. (1966), other researchers have tried to correlate teacher qualities with student achievement; data limitations limited analysis mainly to teacher experience, graduate degrees or licensing (Hanushek, 1997; Hedges, Laine and Greenwald 1994; Goldhaber and Brewer, 2004; Goldhaber and Anthony, 2005).

Rice's (2003) research explored teachers as a critical resource in education and stated that "it is the most important school-related resource" (p. v). However, Rice (2003) reasoned that there is scant robust or strong research on how to hire, retain, and promote teachers; and therefore the debate of teachers as an important resource and policy being constructed around teacher characteristics that relate to performance is largely ideological (Rice, 2003, p. v). Subject-specific courses and credentials matter, especially for the high school math teacher, but these two characteristics are insufficient; delivery and practice applying that knowledge in the classroom is what is critical (Rice, 2013, p. 51). "Questions relating to whether an intervention is worth the investment can be answered only with good information on the size of the effect and the magnitude of the cost" (Rice, 2013, p. 52).

One of the most recent empirical studies focused on the use of teacher fixed effects in an equation to explain the variation in student achievement (Clotfelter et al., 2007).

Emerging from such studies is the general consensus that a one-standard

> deviation difference in the quality of teachers as measured in this way generates about a 0.10 standard deviation in achievement in math and a slightly smaller effect in reading (Rivkin, Hanushek & Kain, 2005; Rockoff 2004; Aronson, Barrow & Sanders 2003, as cited in Clotfelter et al., 2007, p. 3).

At the elementary school level, Clotfelter et al. (2007) embarked on a longitudinal study to determine the influence of teacher credentials on student achievement, using North Carolina statewide data (3rd, 4th and 5th grade levels for students in years 1995-2004). This elementary school level assessment of teacher quality included several categories: (a) teacher credentials, (b) teacher characteristics, (c) student characteristics, and (d) classroom characteristics. The study revealed that the greatest impact on student achievement related to years of teacher experience followed by teacher license type (in NJ terms–alternate route, provisional, or standard license) and teacher test scores on licensing exams but not the teacher's possession of an advanced degree. The greatest influence of teacher quality was on student math scores rather than on student reading scores (Clotfelter et al., 2007). Teacher years of experience at the elementary level was the most significant effect size reported: "peak range of 0.092 to 0.119 standard deviations after 21-27 years of experience, with more than half of the gain occurring during the first couple of years of teaching" (Clotfelter et al., 2007, p. 27). State licensing exam scores were found to have a significant and positive correlation to student achievement; "teachers whose test scores were one standard deviation above the average would increase student achievement by 0.011 to 0.015 standard deviation" (Clotfelter et al., 2007, p. 28). As for teacher graduate degrees at the elementary school level, Clotfelder et al., (2007) found a negative effect on student achievement for those with master's degrees or higher. Graziano (2012, p. 78) quoted Clotfelter et al. (2007) as stating that "higher degrees might be important at the secondary school level."

That research finding was not corroborated in Clotfelter et al. (2007) but something similar was found in Clotfelter et al. (2010). Unlike elementary school teachers, at the high school level teachers having master's degrees reflect a "small positive coefficient of 0.004" on achievement but teachers with Ph.D.'s have a "0.09 negative" effect on student achievement (Clotfelter, 2010, p. 667). Graziano (2012) confirmed that "faculty mobility and MA+ are statistically significant predictors for HSPA Math performance (*F* change = 6,968; df = 2,326; and p <.001" (p. 140).

At the high school level, Clotfelter et al. (2010) also established that the most significant student achievement gains were ascribed to the first five years of teaching—"3-5 years effect size of 0.0608"—and beyond five years of teaching little is gained at the high school level in contrast to the elementary school teacher, where the teaching years of experience beyond five matter (p. 666).

Other teacher credential factors analyzed by Clotfelter et al. (2010) at the high school level revealed that teachers from a very competitive undergraduate college added 0.0188 to student achievement; this meant that the quality of one's undergraduate institution mattered in predicting student achievement. However, the most important statistic relates to teacher test scores on math and biology.

> A one-standard deviation difference in a teacher's math test score is associated with a quite large and statistically significant 0.0472 standard deviation difference in student achievement in either algebra or geometry. The teacher test score in biology is also predictive of student achievement in biology but with a smaller coefficient. Being certified in math increases the achievement of a teacher's students in a math course on average by about 0.11 standard deviations (Clotfelder et al., 2010, p. 669).

Teachers recognize that it is easier and more rewarding to teach students from advantaged backgrounds as opposed to students from disadvantaged backgrounds; therefore, highly qualified teachers are incentivized to teach in areas with large, more advantaged student populations (Clotfelter et al., 2007). One of the biggest problems that schools in poorer districts face is a shortage of qualified teachers. “Experienced teachers often leave these schools, and many good teachers avoid them” (Morgan, 2012, p. 292).

New Jersey’s historical report card data list the percentages of faculty and administrative members in the school who hold a bachelor’s, master’s, or doctoral degree as a total aggregate variable (NJDOE, 2011). All administrators in the state of New Jersey must possess a master’s degree or higher in order to be eligible for certification. Therefore, because the NJ Report Card data do not separate teaching faculty from administrators, the data cannot accurately analyze school level data exclusively for teacher credentials but must include total staff. The preponderance of literature analyzes teacher credentials and not administrator credentials. Nevertheless, Graziano (2012) reported that “schools with a higher percentage of teachers with a master’s degree or higher perform better on the NJ HSPA Math than schools with a lower percentage of teachers with a master’s degree or higher (p. 145).

School Variables

Student-Faculty Ratio

The student/faculty ratio is calculated by dividing the reported October school enrollment by the combined full-time equivalents FTEs (FTEs include guidance counselors, etc.) of classroom teachers and educational support services personnel assigned to the school as of October of the school year (NJDOE, 2011). Pupil-teacher ratio has been used to minimize actual class size in some research (Underwood & Lumsden, 1994). Achilles (2012) points out that this measure is not one that should be confused with average class-size. This was affirmed by Aud, Bianco, Fox, Hussar, Planty, and Snyder (2010). “Student-teacher ratios do not provide a direct measure of class size” (p. 96).

Aud et al. (2010) detailed statistical ratio data: “The student-teacher ratio for all regular public secondary schools increased between 1990–1991 and 1996–1997 (from 16.7 to 17.6) and then declined to 16.4 in 2007–2008” (p. 96). The study shared that smaller schools tended to have lower student-teacher ratios compared to larger schools. For instance, “regular public secondary schools with 1,500 students or more enrolled, on average, 6.1 more students per teacher than regular public secondary schools with enrollments under 300 students per teacher than regular public secondary schools with enrollments under 300 students” (Aud et al., 2010, p. 96).

The National Assessment of Educational Progress (NAEP) provides information on long-term trends in reading and mathematics achievement of 9-, 13-, and 17-year-olds in the United States (Aud et al., 2010, p. 54). Although the “data have been collected every two to five years since 1971 for reading and since 1973 for mathematics” (Aud et al., 2010, p. 54), it has not been related or reported to reflect a comparison to student/teacher ratios.

Rodriguez (2014) looked at parental involvement and student-teacher ratios as a predictor of a school’s effort to partner with parents of children receiving special education services (p. 69). The researcher, Rodriquez’s (2014), results indicated that “student-teacher ratio was the strongest predictor of parents’ perceived school engagement efforts” (p. 69). In this study, n=63 for the high school level reports a minimum student-teacher ratio of 14.92 and a maximum of 23.77. However, in this study the student-teacher ratio was calculated as the total reported number of students divided by the total reported number of teachers and not total staff, which makes it a very different calculation than the data set used on the NJ Report Card. Therefore, little from this study can be garnered from or compared to the NJ Report Card variable used in my study.

Average Class Size

Average class size for secondary schools (9-12) is based on the total enrollment per grade divided by the total number of English classes for the same grade. For secondary grades, the state average is the total enrollment for each grade divided by the total number of English classes for the same grade (NJDOE, 2011).

> Differing formulas for counting students and teachers are a major impediment to understanding and using small classes correctly: a pupil-teacher ratio (PTR) is a division problem; class size is an addition problem. The two are not the same, and thus PTR data cannot be used as a substitute for actual class-size data (Archilles, 2012, p. 1).

Note that average class size is not actual class size. Thus the variable does not represent actual class size, but it is the only class size variable available. The seminal work on actual class size was conducted in Tennessee. Project STAR (Student Teacher Achievement Ratio) was a statewide, large-scale longitudinal (1985-1989) experiment of small-class effects on the achievement and development of pupils in Grades K–3. Mosteller (1995) concluded, "The Tennessee class-size project, a controlled experiment . . . is one of the most important educational investigations ever carried out." (p. 113).

The size of the STAR educational experiment included 11,600 students and 340 teachers in 79 schools (Achilles, 2012). Students and grade-appropriate teachers were randomly assigned to (a) a cohort, small classes (15-17), (b) regular classes (22-25), or (c) a third group of regular classes with a full-time teacher aide. Students who moved or who were retained in grade were randomly replaced. Students in the small cohort groups outperformed the regular classes each year in test scores and non-cognitive measures such as behavior and attendance; they were less likely to be retained or drop out of school. The gains for the smaller cohort students were cumulative and even greater or directly proportional to the years spent in smaller classes (a maximum of four years). However, the focus of the proven study of short and long term benefits refers to early childhood education, with small class sizes of 15-17 at the K-3 grade levels only. The long-term effects of this experiment are critical and support high school success.

Achilles (2012) documented the long-term effects of K-3 small class sizes:

- Reduced Black-White gap in college entrance test taking by 54%
- STAR students more likely to take SAT and ACT tests
- Increased the odds of high school graduation by about 80% for those who were in STAR for four years
- For students from low-income homes, three years of small classes increased the odds of graduating by approximately 67%
- Small-class participation had a significant positive impact on the amount of foreign language courses taken, and the highest levels taken in foreign languages and mathematics. The effect sizes were small but noteworthy (p. 2)

Educational policymakers have justified reducing class size since 1978 based on the Glass & Smith study, *Meta-Analysis of Research on the Relationship of Class-size and Achievement.* The Glass & Smith (1978) collected data from 900,000 students covering research for more than 70 years in twelve countries (class sizes ranged from 1-65 and achievement differentials spanned from 0.551 to 0.030, p. 35). Phelps (2011) re-analyzed Glass & Smith's work using regression analysis to make comparisons between achievement and class size. Because the raw data from Glass & Smith (1978) was not available in electronic form and transcription was labor intensive, Phelps (2011) used only elementary school class data considered the most relevant: reading, mathematics, and language. Phelps (2011) re-analysis established the following:

> The evidence supports the notion that class sizes over a certain size are associated with a decrease in achievement; the exact critical point is in doubt based on these data and analyses. In contrast, the evidence does support lowering class sizes from the large extremes, and there are indications that the potential gain would offset the marginal cost. The influence of class size between about 15 and about 45 is unclear, other than the general conclusion that the relationship between achievement and class size is indeed complicated . . .. Determining the amount of variance explained by class size is complex because class size is likely to be correlated with other important variables such as socioeconomic status (SES), expenditures, teacher qualifications, support staff, and instructional materials. Studies with these variables could provide estimates of possible ranges of the variance attributable to class size; these estimates can be instructive in policy decision-making . . . the financial cost of reducing class size as a primary method of increasing achievement is not warranted (Phelps, 2011, pp. 12, 13).

Unfortunately, Phelps (2011) did not recognize the difference in the Glass & Smith (1978) student population or data elements in comparison to the STAR small class parameters or he would not have concluded that small class sizes lack effect. Clotfelter et al., (2007) used average class size and found the reduction in class sizes at elementary grades "by five students would increase student achievement by about 0.010 to 0.015 standard deviations on average" (p.

29). Again, average class size is not class size, and thus the influence of average class size is 1/10th that of actual class size. Regrettably, the New Jersey Department of Education bureaucrats do collect actual class size data, and thus, that variable is rather meaningless to make fine-grained decisions.

Length of School Day

Patall et al. (2010) sum up the frenzy among policymakers regarding increasing the length of the school day or year: "Policymakers are drawn to using time as a lever for reform even though no guarantee of improved student learning exists . . . the cost to states are estimated at $2.3 to $121.4 million for each additional day for school." (p. 3). *A Nation at Risk: The Imperative for Educational Reform* called for 180 to 210 days but the least cost effective strategy for education reform was increased time (p. 4). Tienken and Orlich (2013) stated that *A Nation at Risk* "was an intellectually vapid and data-challenged piece of propaganda but that did not stop public servants from creating reform movements based on the report" (p. 31).

President Obama commented on increasing learning time in schools:

> We can no longer afford an academic calendar designed for when America was a nation of farmers who needed their children at home plowing the land at the end of each day. That calendar may have once made sense, but today it puts us at a competitive disadvantage. The challenges of a new century demand more time in the classroom (as cited in Farber, 2011, p.3).

Time matters. How much or how little depends greatly on the degree to which it is devoted to appropriate instruction. According to Patall (2010), the majority of studies dealing with the relationship of education time to student achievement looked at the total number of school days or hours students are required to attend school, while other studies focus on engaged time or academic instructional learning time. In some cases the time variable was not clearly specified. These inconsistencies made it difficult to make comparisons. Mixed findings about the degree to which time influences student learning complicates the issue. Despite this, the literature revealed a fairly consistent pattern (Patall et al., 2010, p. 3):

1. There is little or no relationship between allocated time and student achievement.
2. There is some relationship between engaged time and achievement.
3. There is a larger relationship between instructional time and achievement.

In another meta-analysis extra time did not in itself make a difference; rather it was how the extra time was used. For schools, this means “maximizing the time during which students are actively and appropriately engaged in learning,” or what is often simply called “time on task” (Aronson, Zimmerman, and Carlos, 1998, p. 3; Walberg, 1988, p. 85).

One of Secretary of Education Arne Duncan’s key strategies for fixing public schools surrounds his philosophy. “add more school time on task by lengthening the 6.5-hour school day and the 180-day school year” even though researchers fear that the current upsurge of expanding learning time will show meager results related to positive effects on student achievement, as past results will predict the future results (Silva, 2012, p. 1). “Correlation analysis of state time policies and achievement scores finds that states that require more time don’t perform any better or worse than those that require less or don’t set requirements” (Silva, 2012, p. 2). In fact “reviewers have repeatedly suggested that longitudinal and experimental studies in which allocated time is manipulated are needed to draw causal conclusions about the impact of lengthening the school year or school day” (Patall et al., 2010, p. 413). Therefore, they concluded that further research is suggested; “even the correlational evidence remains problematic in that little variability in the lengths of the school year and school day exists across districts" (Caldwell, Huitt, & Graber, 1982; Funkhouser et al., 1995; Mazzarella, 1984, as cited in Patall et al., 2010, p. 413). Pedersen (2011) cited Farbman & Kaplan (2005) and reported that "nations with more than 180 instructional days and/or who have calendars that are year-round have outperformed American Schools" (p. 7). Furthermore, Pedersen (2011) shared that although the number of states implementing year-round schools in the United States increased, data determining effectiveness remain limited, particularly at the high school level. Cooper, Valentine, Charlton, and Melson (2003) conducted a meta-analysis on schools that do not have a long summer break and uncovered ambiguous results:

> The quality of evidence on modified calendars is poor. Within this weak inferential framework, the average effect size for 39 school districts was quite small, d = .06, favoring modified calendars. Studies that used statistical or matching controls revealed an effect size of d = .11 (p. 1).

However, Cooper et al. (2003) discovered statistical significance: "Students from poorer communities attending modified calendar schools outperformed their traditional calendar counterparts by about .20 standard deviation" (p. 40).

Pedersen's (2011) study compared performance gains between year-round public school calendars for 26 high schools in California, Illinois, and Texas against high schools on traditional calendars. According to Pedersen (2011), performance gains on standardized language arts and math exams at the high school level could not be supported as a result of increased time; in fact, "traditional-calendar high schools consistently outperformed their year-round peers . . . from the academic years of 2007 to 2010" (p. 75).

Patall et al. (2010) prepared a systematic review of all the research from 1985-2009 on the length of the school day and located 15 research studies (See Table 4). The following chart has been adapted from their findings.

Table 3

Extending the School Day/School Year, Review of Educational Research 1985-2009

	Author (s) Year	Study - School Level	Design	Reason for Elimination	Strengths/ Weaknesses	What Results Mean	Effect Size
1	Adelman, Haslam, & Pringle (1996)	Middle school 1 school & Elementary School	Case Study	Eliminated because it is a case study		n.a.	Overall student outcomes remained poor with extended year
2	Bishop, Worner, & Weber (1988)	High School Grade 8-12 1 school	Cohort (compared one school year of regular length day with year of lengthened day/ Surveys)		Redundancy in sample between cohorts	Added 7th period to school day	
3	Wheeler (1986-1987)	Grade 6 75,000 students 1,030 Schools	Correlational (California) Length of school day	Eliminated due to grade level			Scores: Reading $p<.01$ Writing $p<.01$ Math $p<.01$
4	Brown (1998)	Kindergarten	Quasi-Experimental	Eliminated review due to grade level		n.a.	
5	Frazier & Morrison (1998)	Kindergarten	Quasi-Experimental	Eliminated review due to grade level		n.a.	
6	Green (1998)	Elementary, Middle and High School 25 Schools	Quasi-Experimental Pre-Post Test	Eliminated because of pre/posttest method		n.a.	
7	Meier (2009)	Grades 3 & 4	Quasi-experimental (Dissertation)	Eliminated review due to grade level		n.a.	
8	Pittman, Cox, & Burchfiel (1986)	Grades 4-8	Cohort – 1976/1977 inclement weather caused 10-20 days shorter school year, compared to other school years 1972-1979	Eliminated due to inconsistency in data years	Discrepancy between number of days in school used in comparison		
9	Sims (2008)	Grades 4, 8, 10 1227 districts	Correlational 2001 law restricted school yr start to after 9/1				Scores: Math $p <.05$ Language Arts $p <.05$ Reading $p<.05$
10	Van der Graaf (2008)	Grade 3 841 Students 2 schools	Quasi-Experimental	Eliminated due to grade level		n.a.	
11	Farbman & Kaplan (2005)	Elementary and Middle Schools 8 schools	Case Study	Eliminated because it is Case Study		n.a.	
12	McDonald, Ross, Abney, & Zoblotsky (2008)	Grades 5 to 8 330 Students	Quasi-experimental	Eliminated not a public school setting		n.a.	
13	New York City Board of Ed (2000)	Grades 3-7	Quasi- Experimental	Eliminated due to grade level & because it is a report / policy		n.a.	
14	Robin (2005)	Preschool	Dissertation	Eliminated due to grade level		n.a.	
15	Ross, McDonald, Alberg, & McSparrin-Gallagher (2007)	5th Graders 98 students	Quasi-Experimental	Eliminated not a public school setting		n.a.	

Note. Adapted from " Extending the School Day or School Year: A Systematic Review of Research (1985-2009)," by E. Patall, H. Cooper and A.B. Allen, 2010, *Review of Educational Research, 80,* p. Appendix. Copyright by Copyright Holder. Reprinted with permission Sage Publications.

Length of Instructional Day

Corey, Phelps, Ball, Demonte, and Harrison (2012) conducted a large-scale study to explain the variation in instructional time to further the discussion and research related to educational improvement-based reforms. The focus of their study was on the effects of various interventions on the amount of instruction students actually receive. The research of Corey et al. (2012) revealed the following:

> [When they] examined the characteristics of classrooms and schools that are related to students' time in instruction, with a focus on how whole school interventions can increase students' access to instruction in English language arts and mathematics, substantial effects were found when using quartile regression to estimate the effects at the lower end of the distribution of instructional time (pp. 146, 147).

The complexity of the instructional day emphasized the following:

> "Achievement differences . . . reflect the differences in the percent of time on task in the classroom. Apathetic learners in the classroom who spend a minimum of time on the task cannot be expected to learn as much as learners who are actively engaged in the learning process during most of the class time" (Coleman et al., 1966, as cited in Bloom, 1976, p. 687).

Eren and Millimet (2007) reported on results in a Texas study using three test scores in math, reading, social science, and science from Grades 8, 10, and 12 culled from the National Education Longitudinal Study of 1988 database:

> School year length and the number and average duration of classes affect student achievement. However, the effects are not homogeneous– in terms of both direction and magnitude–across the distribution (p. 301).

The statistics in the study by Eren and Millimet (2007) indicated a longer school year would have a negative impact on student test scores: “A longer school year ($\tau 180+ = -0.088$, *s.e.* = 0.148)” (p. 313). However, Eren and Millimet (2007) also found “a positive impact of structuring the school day to include more class periods ($\tau 7 = 0.267$, s.e. = 0.157; $\tau 8+ = 0.262$, s.e. = 0.208)” (p. 313). In the final analysis, Eren and Millimet (2007) determined that the “effect of changing from the modal organizational structure (six or fewer classes that on average last 51 minutes or more) to seven classes that last 45 minutes or less raises student test scores by roughly (0.267 + 0.745 ~=) one point (p. 313). Eren and Millimet (2007) postulated that students could be sorted into different structures for length of the school year or the school day to optimize learning and maximize test performance (p. 331).

School Size

Primarily smaller high schools were formulated to enhance the student feeling of being connected. The premise is that increased feelings of being connected have been studied and proven by several researchers to increase achievement (Cotton, 1996; Lee & Smith, 1997; Leithwood & Jantzi, 2009, as cited in Carolan, 2012, p. 583). However, according to Weiss, Carolan, and Baker-Smith (2010) who analyzed school size related to student engagement and academic achievement, “small student groups tend to exacerbate already extant disadvantages among adolescents” but also “that there are potentially harmful changes when cohorts grow beyond 400” (pp. 173, 163). Furthermore, Weiss et al. (2010) concluded that moderately-sized groups of 400 students offered the largest benefits; their research mirrors other findings. Although smaller groups enhance student engagement, the smaller sizes do not translate into greater academic achievement and emphasize that “no school or cohort size will optimize outcomes for all students” (Weiss et al., 2010, p. 173).

Tramaglini (2010) studied K-12 districts (n=261) to reconfirm the relationship between school size and achievement at the district and high school levels in New Jersey. The analysis by Tramaglini (2010) sustained the validity of previous studies, "indicating that a statistically significant negative relationship exists between high school enrollment size, district enrollment size, and student achievement" (p. 35). More specifically, Tramaglini (2010) found negative relationships between school district size and HSPA mathematics "*-0.205*" as well as language arts at "*-0.190*" (p. 33). Furthermore, Tramaglini (2010) suggested that consolidating New Jersey schools and/or regionalization could negatively impact high schools which are categorized in the lower socioeconomic status spectrum. "As high school enrollment size increases in New Jersey lower socioeconomic schools, student achievement in language arts and mathematics on the HSPA appears to decrease" (Tramaglini, 2010, p. 34).

Theoretical Framework

In this study, I examined school inputs to determine the influence of the length of the school day on Grade 11 NJ High School Proficiency Assessment (HSPA) scores in Language Arts (LA) and Mathematics (M) for the year 2011. Because production function involves mathematical calculations, statistical analyses of inputs (staff, student, and school factors) were specified to assess the amount of variance exerted on the output measure (NJ HSPA scores).

America has been dazzled by scientific management and has tried to employ these constructs to education. Frederick Taylor has been credited as engineering the concept of scientific management. As Callahan (1962) most aptly put it, scientific management was seen as " a means whereby production could be increased, wages raised, and prices lowered" (p. 19). "Educational outputs are influenced by a political process that can respond to local differences in demand for public education in both budgetary (input) and output dimensions" (Klein, 2007,

p. 2).

In the 1960s, educational production function was suggested as a viable approach to educational research. For decades, the controversy over whether per-student expenditures link to student achievement has been debated. Klein (2007) stated that “a . . . student’s demographic characteristics and family background better explain their performance on standardized tests than do measures of the resources devoted to their education” (p. 3). Hanushek’s (1986) review of studies concluded that per-student expenditures are weakly linked to student achievement and disappear when differences in family background are taken into account (Klein, 2007).

Conclusion

Hoyle, O’Dwyer, and Chang (2011) reported on a longitudinal study conducted for Maine’s Department of Education that analyzed the state’s high school assessment against factors suspected to impact student test scores. Although school factors such as race, socioeconomic status, and the proportionate number of teachers to students in schools was considered, the variables in the study never included length of the school day and the impact on test scores. Despite conventional wisdom that school inputs make little difference in student learning, a growing body of research suggested that schools can make a difference, and a substantial portion of that difference is attributable to staff, student, and school factors.

Jacob and Rockoff (2012) suggested reorganizing schools by making three structural changes to increase student achievement without significant funding investments:

- Starting schools later for middle school and high school students
- Using K-8 schools rather than junior high or middle schools or taking other steps to minimize the disruptive transitions
- Assigning teachers to the same grades and subjects from year to year

The suggested change in starting times is research based: "Medical research documents important changes in the circadian rhythm during adolescence that shift children's internal clocks to later bed and wake times (Jacob & Rockoff, 2012, p. 29). These same researchers found evidence to support this assertion:

> Middle-school aged children learn better in K-8 schools than they do in separate 6-8 or 7-8 schools. For example, in both Florida and New York City, as students entered middle schools, their test scores declined markedly relative to the scores of students in K-8 schools.

Last, Jacob and Rockoff stated the following:

> [Because] teachers represent one of the most important inputs in a child's education, one of the few predictors of teacher effectiveness, particularly in the first few years of teaching, is experience. Jacob and Rockoff provide evidence that teachers may gain experience more quickly by teaching the same subject and the same grade in back-to-back years early in their careers.

Introduced by Kober (2012) was the statistic that "two-thirds of African American and Latino students attend schools in which more than 50% of the students are from low-income families and less than one-fourth of White students attend schools with poverty rates this high" (p. 8). The most significant factor that affects student achievement, in all the empirical research reviewed, is student/family socioeconomic status; Abrams and Fong (2012) confirmed this especially as it relates to parent income, parent occupation, parent education level, and family structure. Students in the lower socioeconomic status on free or reduced lunch are the ones that will benefit most assuredly from strategies that address inputs/predictor variables that reduce achievement deficits: having better quality teachers with more experience and higher Praxis scores, reducing teacher mobility, improving student attendance, reducing student suspensions, creating smaller class size, cohort groups at the K-3 grade levels, and increasing student instructional engagement time. The variables that potentially hold significance for improving student achievement for lower socioeconomic students may not be wise educational investments for students who come from wealthier families. Chmelynski (2006) writes about a middle school success story in Roxbury, Massachusetts. This district's middle school was the lowest performing and transformed itself into one of the highest performers by instituting 90 minute core class time and reducing time in non-core subjects to 50 minutes; this strategy added 35 days to the school year. Roxbury is a low-income urban section of Boston; approximately 64% of the population is represented by African American minorities, and 23% are non-English speakers (http://www.areavibes.com/boston-ma/roxbury/demographics/). Cooper et al. (2003) reaffirmed that higher achievement occurs for disadvantaged students who attend schools that follow a modified school calendar (schools that do not have a long summer break) and that the effect of modified calendars on achievement might be cumulative.

Regarding the implementation of education policy changes "using the general conceptual framework to formulate educational policy does not automatically result in a single set of practices guaranteed to work" (Wilson, Kauffman, & Purdy, 2011, p. 7). Lucio, Rapp-Paglicci, and Rowe (2011) emphasized that empirical evidence points to the fact that student achievement issues are cumulative, can be observed early and are "a consequence of multi-dimensional interacting factors, including family, community, school, peers, and individuals" (p. 154). Further, Lucio, et al. (2011) suggested that early interventions can mitigate negative later outcomes such as dropping out of high school.

Although LEP students tend to have lower SES status and attend schools with high concentrations of poverty, LEP overall tends to only moderately impact academic performance (a stronger relationship on achievement for Grades K-3 and a weak effect on Grades 4-12). This study analyzed that variable, but I suspected there was a good chance that, as the variable was also tied to SES, the results might reveal a significant relationship to scores on the NJ HSPA; however, other research found that it is not an accurate predictor of achievement.

Eight million children in the United States have been classified with a disability (Mamlin &Harris, 1998), and they are usually in a low socioeconomic status grouping. Over six million children in the United States currently receive services under IDEA (Federal Education Budget Project (FEBP), 2011b). Bassiri & Allen's (2012) analysis suggested that the better way to assess achievement of LEP and IEP students is through student growth models and not standardized testing.

Of most notable importance and reported by the National Center for Education Statistics (NCES) is the following:

> The performance of 17-year-olds on the 2008 reading and mathematics assessments was not measurably different from their performance in the early 1970s. The average reading score for 17-year-olds was higher in 2008 than in 2004 but was not significantly different from the score in 1971. In mathematics, the average score for 17-year-olds in 2008 was not significantly different from the scores in either 2004 or 1973" (Aud et al., 2010, p. 56).

Very few studies have been conducted on the NJ HSPA and the NJ School Report Card variables. The length of the school day variable has not been studied at the New Jersey elementary or secondary school level, perhaps because the variation in New Jersey schools is relatively small; nevertheless, a comparison between length of school day and instructional time, based on school DFG designations, should be conducted to determine if SES and that variable influences achievement. It was likely the analysis of New Jersey's report card variables would be consistent with other research findings.

The bottom line is we need to maximize our understanding of what contributes to student success. If high-poverty schools need more school time to counteract negative test results and strengthen student achievement and the findings are empirically sound, then we must as educators support that.

CHAPTER III

METHODOLOGY

Research Design

According to Johnson (2001), quantitative educational research is predominately non-experimental because randomized experiments or quasi-experiments are not viable. Therefore, since it is impractical or improbable to manipulate many variables in educational settings but the need to study independent variables is nevertheless great, educational researchers must revert to using the acceptable practice of explanatory studies (Johnson, 2001, p. 3). I used this accepted practice to conduct a correlational, explanatory design with quantitative methods. Johnson (2001) further describes the concept of explanatory research as having the following goal-directed criteria: (a) were the researchers trying to develop or test a theory about a phenomenon to explain 'how' and 'why' it operates, and (b) were the researchers trying to explain how the phenomenon operates by identifying the causal factors that produce change in it? (p. 9).

This was an explanatory, non-experimental study using correlation research and hierarchical multiple regression analysis (at a single point in time) to measure the relationship between two variables: length of school day and Grade 11 NJ 2011 HSPA scores. The analysis provides quantitative descriptive research on the relationship of length of school day in New Jersey secondary school Grade 11 students in "A-J" districts and scores on the NJ Grade 11 2011 HSPA.

Determining which student and school variables had a statistically significant relationship to student achievement required the use of simultaneous multiple regression and hierarchical regression models. According to Witte & Witte (2007), multiple regression models are "accompanied by standard errors of estimate that roughly measure the average amounts of predictive error" (p. 165). Furthermore, Leech, Morgan, and Barrett (2011) state the following:

1. Both simultaneous regression and hierarchical multiple regression require that you specify exactly which variables serve as predictors, and they provide significance levels based on this number of predictors" (p. 106).
2. The assumptions for multiple regression analysis include the following: that the relationship between each of the predictor variables and the dependent variable is linear and that the error, or residual, is normally distributed and uncorrelated with the predictors (p. 107). A Durbin-Watson backward analysis was run to ensure the residuals from the linear regression or multiple regression model variables were independent.
3. Hierarchical multiple linear regression models were used "when you want to enter the variables in a series of blocks or groups . . . this method is intended to control for or eliminate the effects of a variable on the prediction" (p. 121).
4. The need to confirm test scores for normalcy is required. Skewness measures the degree and direction of asymmetry. A symmetric distribution such as a normal distribution has a skewness of 0, and a distribution that is skewed to the left, e.g. when the mean is less than the median, has a negative skewness (Field, 2013, p. 21).

There is disagreement among researchers on whether transforming data is needed (Field, 2012); the discussion on transformation of variables is expanded upon in the data analysis section of this study.

Nevertheless, multiple linear regression models were used in this study to explore the relationship between the outcome variable (NJ HSPA scores in Math and LAL) and predictor variables (in the categories of student, school, and staff).

Methods

A quantitative approach was chosen for this study. "Certain types of social research problems call for specific approaches . . . if the problem calls for . . . the identification of factors that influence an outcome . . . then a quantitative approach is best" (Creswell, 2009, p. 18).

A multiple regression analysis (multivariate) was used in this study to analyze and interpret the public high school report card data (2011) found on the New Jersey Department of Education (NJDOE) website. According to Leech et al. (2011) when the researcher desires to answer complex associational questions involving two or more independent variables (student, teacher, and school variables contained on NJ Report Cards) and one dependent variable (in this case, NJ HSPA scores), then the appropriate statistical analysis of multiple regression is apposite (pp. 86, 87). The objective of the multiple regression analysis was used to find a linear relationship between the dependent variable (NJ HSPA scores) and several independent variables (student, teacher, and school variables). An analysis of the factors commonly associated with student achievement were identified and discussed in Chapters I and II: (a) Student Variables–Student Attendance Rate, Student Suspension Rate, Student Mobility Rate, Percentage of Students on Free or Reduced Lunch, Percentage of Students with Limited English Proficiency, Percentage of Students with Disabilities, (b) Staff Variables–Faculty Attendance Rate, Faculty Mobility Rate, Percentage of Staff with Master's Degree or Higher, and (c) School Variables–Student Length of School Day in Minutes, and School Size. The regression models allowed the researcher to explain the variation in the dependent variable (NJ HSPA aggregate achievement scores). The length of the school day in minutes is the prime predictor variable studied.

Regression techniques only establish relationships, not causation. However, regression analysis and models explain the of amount variation in the dependent variable (HSPA scores) predicted by the independent variable. An analysis of the statistical significance (or probability level 'p') as well as effect size (strength of the relationship between the independent variable and the dependent variable was ascertained.

> One method of expressing effect sizes is in terms of strength of association. The most well known variant of this approach is the Pearson Correlation Coefficient, r . . . it has been common to use R^2 (r squared) because it indicates the percentage of variance in the dependent variable that can be predicted from the independent variable(s), (Leech et al., 2011, p. 91).

R^2 ranges from 0 to 1 and is interpreted as the percentage of the variance in the dependent variable (NJ HSPA scores) that is explained by the independent variables (staff, student, and school variables). Furthermore, Leech et al. (2011) established that "hierarchical linear regression models enable one to model nested data (data in which certain variables are present only in a subset of one's data) over time" (p. 87). Hierarchical linear modeling (HLM) should not be confused with hierarchical multiple regression (HMR). Illustrating the nature of length of the school day with hierarchical multiple regression adds variables to the regression model in stages. At each stage, an additional variable(s) was (were) added to the model, and the change in R^2 was calculated. A hypothesis test was done to test whether the change in R^2 was significantly different from zero. In hierarchical multiple regression analysis, the researcher determined the order in which variables were entered into the regression equation. The researcher may want to control for some variable or group of variables. The researcher performed a multiple regression with these variables as the independent variables. From this first regression, the researcher accounted for the variance in the corresponding group of independent variables. The researcher ran another multiple regression analysis including the original independent variables and a new set of independent variables. This allowed the researcher to examine the contribution above and beyond the first group of independent variables. The F statistic allowed the researcher to determine whether the model was statistically significant.

The purpose of this quantitative study was to explain the influence of length of school day on Grade 11, 2011 NJ HSPA scores and school variables found in the extant literature and aggregate district student NJ HSPA scores in Grade 11 Math and Language Arts. By focusing on multiple schools and student scores, in both language arts and mathematic for Grade 11 NJ HSPA in the 2010-2011 school year, this study aimed to produce research-based evidence to assist all stakeholders in public education regarding reform initiatives. Scant empirical evidence, particularly related to the length of the school day, created a void in the literature that the researcher expected to fill. The chosen student, faculty, and school variables and the relationship of these variables to achievement are briefly explained in Chapter II of this study.

The overarching research question used in this study asks: What is the influence of length of school day on the Grade 11, 2011 New Jersey state-mandated High School Proficiency Assessment (HSPA) scores when controlling for student, school, and administrative variables?

Data Collection

The New Jersey Department of Education (NJDOE) provides public access to data and resources that were used in this study. The data used for this study were collected from the New Jersey sample population for the 2010-2011 school year for Grade 11 high school students in the

“A-J” DFG categories (NJDOE, 2011). The purpose of using public data was to provide generalizations from the sample population in order to make inferences about the length of school day and NJ HSPA exit exam scores (Babbie, 1990, as cited in Creswell, 2009, p.146).

The results for the 2010-2011 NJ HSPA was located under community information, DOE Archives, Historical Report Card Data, 2011 New Jersey School Report Card (issued March 2011); the Microsoft Excel Zipped, Report Card (RC11) was the data used in this study.

After identifying all New Jersey comprehensive public high schools in the NJ Report Card (RC11), the researcher downloaded the data into a new Excel spreadsheet, including each independent variable mentioned above and in Chapters I and II. The dependent variable data (percentage of students in a New Jersey comprehensive high school receiving either a Proficient or Advanced Proficient score on the literacy arts and mathematics sections of the HSPA) were also downloaded into this same Excel spreadsheet. The data were matched by school and district and copied into aforementioned Excel spreadsheet for further analysis. Because the RC 11 includes all school levels, only high school data records were entered into the new Excel spreadsheet and cross-referenced by school and district. The Excel spreadsheet allowed the researcher to organize student achievement data on the HSPA in Language Arts and Mathematics scores by school. Following the organization of the data into an excel spread sheet a correlational design was used to determine relationships between the report card variables and student achievement on the HSPA.

Because the results of this study were derived from the school level data obtained from the NJDOE database for Grade 11, 2011 NJ HSPA scores, generalizations might not be appropriate for schools and school districts in different states using other high school exit exams.

Sample Size/Data Source

The sample size exceeded the minimum requirements for simultaneous and hierarchal regression as defined by Field (2009), who referenced Green (1991).

> If you want to test the model overall, then he (Green) recommends a minimum sample size of 50 + *8k*, where *k* is the number of predictors. So, with five predictors, you'd need a sample size of 50 + 40=90. If you want to test the individual predictors, then he suggests a minimum sample size of 104 + *k*, so again taking the example of 5 predictors you'd need a sample size of 104 + 5 = 109 (Field, 2009, p. 222)

I developed an initial simultaneous regression model using the predictor variables associated with the three distinct categories of staff, student, and school. Simultaneous regression models were run on the outcome variables to determine significance. Subsequently based on the analysis, hierarchical multiple regression models were created to determine the r^2 change. Therefore, I needed at least 50 + 8 (6) = n, or a total of 48 cases. The sample size I used (n=326) provided the power to identify an effect size of at least 50 at the 95% confidence interval and to generate results to the remaining schools in the state.

Archived data was gathered from the New Jersey Department of Education databases including NJ School Report Card data that contain NCLB-required assessment information. The sample for this study consisted of schools that reported all required information related to school, staff, and student variables to the NJDOE for 2011. Only public comprehensive high schools in New Jersey associated with District Factor Groupings in eight categories of A, B, CD, DE, FG, GH, I or J were included. Accordingly, only 326 public secondary schools (NJDOE, 2011) were identified for this study; these schools are listed in the appendices section of this research study. Because New Jersey places districts in a District Factor Grouping (DFG) system as a means of ranking school districts by socioeconomic status (SES) the district range labels represented in Table 4 illustrates that an “A” district was among the lowest (poorest) socioeconomic group while a “J” district was among the highest (wealthiest) socioeconomic group. Vocational schools, special services school districts/special education schools, and charter schools (DFG’s R, and V) were excluded from the study to ensure all results obtained from the analysis could be attributed to a typical New Jersey public high school. These schools typically draw students from wider geographic areas, which influence their DFG (socioeconomic) category. Also excluded were DFG “O” categorized schools that house students in the Department of Corrections, Department of Human Services, and the Juvenile Justice Commission (NJDOE, 2011).

Table 4

District Factor Groups in New Jersey, 2011 (A-J only)

	DFG Category	*Number of Schools by DFG*
1	A	52
2	B	36
3	CD	30
4	DE	51
5	FG	44
6	GH	54
7	I	47
8	J	12
	Total	*326*

Statistical frequency models were developed on high school districts of like SES, as well as those that differed, to ascertain an overview of any significant difference in the dependent variable based on socioeconomic status. Since research has shown that socioeconomic status and educational performance are related to educational outcomes, these basic models were run to compare DFG school’s scores included in this study.

Data Analysis

Simultaneous multiple regressions and hierarchical multiple regressions were used in this study. "Multiple regression attempts to predict a normal dependent variable from a combination of several normally distributed and/or dichotomous independent/predictor variables" (Morgan, Leech, & Gloeckner, 2011, p. 140). Tests of normality were used to determine the distribution symmetry of the dependent variable in the sample data. The dependent variable was found to be asymmetrical and therefore the data was transformed using a log10 reflection to create a more normal distribution in order to run further analyses; however, the independent variables were not transformed. Field (2012) indicated that for regression models, the residuals need to be normally distributed, but that the original data values need not be normally distributed; hence, one can deduce that in regression models, there is no requirement that the independent variables be normally distributed. Furthermore, not all researchers support the value of transforming data "the payoff of normalizing transformations in terms of more valid probability statements is low, and they are seldom considered to be worth the bother' (Glass, Peckman, & Sanders, 1972, as cited by Field, 2009, p. 155). As an expert in statistical analysis, Field (2009) cautioned that "we need to know whether the statistical models we apply perform better on transformed data than they do when applied to data that violate the assumption that the transformation corrects" (p. 155). Therefore, statistical models of the transformed and untransformed data were created. The fact that the adjusted R square value for the final hierarchical MA model with the untransformed dependent variable is about 11 percentage points higher than that for the final hierarchical MA model with the transformed dependent variable (69.3% vs. 58.7%) suggests that the regression model using the untransformed dependent variable is superior to (in the sense that it has more predictive power) than the regression model using the transformed variable (See Appendix B).

Univariate Analysis of Variance using both the transformed dependent variable and untransformed dependent variable were performed. Tukey HSD Post Hoc tests were conducted on the major independent variable school day length by creating three bins: short, median, and long and making comparisons among different schools categorized by socioeconomic status (poor, median, rich).

The separate simultaneous linear regression models first determined the significant predictor variables associated with Grade 11 Math and LA scores on the NJ HSPA 2011 exam. The regression model explained the amount of variance in the outcome variable (HSPA scores) that can be explained by the predictor variables. The Pearson correlation coefficient, a measure that conveys change in one variable as it relates to another variable, is represented as r (-1</=r>=+1). The correlation was denoted as high to low in relation to -1 or +1; the sign of r indicates the type of relationship as either a positive or negative relationship (Witte, 2010, p. 133). The direction of the relationship between variables was indicated by a plus or minus sign. “The more closely a value of r approaches either -1.00 or +1.00, the stronger (more regular) the relationship. Conversely, the more closely the value of r approaches 0, the weaker (less regular) the relationship” (Witte, 2010, pp. 134, 135). The “Coefficient of Determination” commonly referred to as R^2 (R square) is used in social science statistics to evaluate the model’s overall influence. R^2 is 1 minus the ratio of residual variability with a 95% confidence interval calculated around the school or district proficiency levels for all subgroups.

Multiple regression models were employed, using HSPA achievement scores as the dependent variable and staff, student, and school variables as the independent variables. The models for the independent variables are as follows:

- Model IV – Hierarchical Multiple Regression for MA to look at the R^2 (square) change
- Model IV – Hierarchical Multiple Regression for LA to look at the R^2 (square) change
- Other models were determined after further SPSS analysis

The following models (See Table 5) were created and used to analyze the variables in the statistical analysis software program SPSS included:

Table 5

Models Analyzed in the Study (Math and LA HSPA Scores)

A. Math HSPA Scores		
I. Tests of Normality on Dependent Variable with Transformed Dependent Variable		
Model I. TPREFLECT Math	Transformed Dependent Variable TPReflect	• HSPA MA Scores
II. Simultaneous Regression		
Model II Math	All Variables, Backward Durbin Watson; used Transformed Dependent Variable	• Faculty Attendance Rate • Faculty Mobility Rate • Percentage of Staff with Master's Degree or Higher • Student Attendance Rate • Student Mobility Rate • Percentage of Students Eligible for Free or Reduced Lunch (SES) • Percentage of Students with Limited English Proficiency • Percentage of Students with Disabilities • Length of School Day in Minutes • School Size

Model III Math	Selected Variables, Backward Durbin Watson - eliminated Student Mobility and Percentage of Students with Limited English Proficiency (LEP) to reduce/extinguish Collinearity; used transformed dependent variable	• Faculty Attendance Rate • Faculty Mobility Rate • Percentage of Staff with Master's Degree or Higher • Student Attendance Rate • Percentage of Students Eligible for Free or Reduced Lunch (SES) • Percentage of Students with Limited English Proficiency (LEP) • Percentage of Students with Disabilities • Length of School Day in Minutes • School Size
III. Hierarchical Multiple Regression Model		
Model IV Math	Selected Variables Entered in the Order of Significance; used transformed dependent variable	• Percentage of Students Eligible for Free or Reduced Lunch (SES) • Student Attendance Rate • Length of School Day in Minutes • Percentage of Staff with Master's Degree or Higher • Percentage of Students with Disabilities
IV. Univariate Analysis of Variance Model		
Model V Math	Transformed Dependent Variable; Binned School Day Length (short, median and long) and Students Eligible for Free and Reduced Lunch (SES) (poor, median, rich)	• Length of School Day in Minutes • Percentage of Students Eligible for Free or Reduced Lunch (SES)
V. Post Hoc Tests		
Model VI Math Tukey HSD	Transformed Dependent Variable; Binned School Day Length and SES	• Length of School Day in Minutes • Percentage of Students Eligible for Free or Reduced Lunch (SES)

Model VII Math Tukey HSD	Transformed Dependent Variable; Binned, SES and Student Attendance Rate	• Student Attendance Rate • Length of School Day in Minutes • Length of School Day in Minutes • Percentage of Students Eligible for Free or Reduced Lunch (SES)
VI. Univariate Analysis of Variance Model		
Model VIII Math	Non-Transformed Dependent Variable; Binned School Day Length (short, median and long) and Students Eligible for Free and Reduced Lunch (SES), (poor, median, rich)	• Length of School Day in Minutes • Percentage of Students Eligible for Free or Reduced Lunch (SES)
B. Language Arts (LA) HSPA Scores		
VII. Tests of Normality on Dependent Variable with Transformed Dependent Variable		
Model I. TPLA_REFLEXT	Transformed Dependent Variable TPLA_Reflext	• HSPA LA Scores
VIII. Simultaneous Regression		
Model II LA	All Variables Backward Durbin Watson using Transformed Dependent Variable	• Faculty Attendance Rate • Faculty Mobility Rate • Percentage of Staff with Master's Degree or Higher • Student Attendance Rate • Student Mobility Rate • Percentage of Students Eligible for Free or Reduced Lunch (SES) • Percentage of Students with Limited English Proficiency • Percentage of Students with Disabilities • Length of School Day in Minutes • School Size

Model III LA	Selected Variables, Backward Durbin Watson - eliminated Student Mobility and Percentage of Students with Limited English Proficiency (LEP) to reduce/extinguish Collinearity; used transformed dependent variable	• Faculty Attendance Rate • Faculty Mobility Rate • Percentage of Staff with Master's Degree or Higher • Student Attendance Rate • Percentage of Students Eligible for Free or Reduced Lunch (SES) • Percentage of Students with Limited English Proficiency (LEP) • Percentage of Students with Disabilities • Length of School Day in Minutes • School Size
IX. Hierarchical Multiple Regression Model		
Model IV LA	Selected Variables Entered in the Order of Significance; used transformed dependent variable	• Percentage of Students Eligible for Free or Reduced Lunch (SES) • Student Attendance Rate • Length of School Day in Minutes • Percentage of Staff with Master's Degree or Higher • Percentage of Students with Disabilities
X. Univariate Analysis of Variance		
Model V LA	Transformed Dependent Variable; Binned School Day Length (short, median and long) and Students Eligible for Free and Reduced Lunch /SES (poor, median, rich)	• Length of School Day in Minutes • Percentage of Students Eligible for Free or Reduced Lunch (SES)
XI. Post Hoc Tests		
Model VI LA Tukey HSD	Transformed Dependent Variable Binned School Day Length and SES	• Length of School Day in Minutes • Percentage of Students Eligible for Free or Reduced Lunch (SES)

Model VII LA Tukey HSD	Transformed Dependent Variable Binned, SES and Student Attendance Rate	• Student Attendance Rate • Length of School Day in Minutes • Length of School Day in Minutes • Percentage of Students Eligible for Free or Reduced Lunch (SES)
XII. Univariate Analysis of Variance		
Model VIII LA	Non-Transformed Dependent Variable; Binned School Day Length (short, median and long) and Students Eligible for Free and Reduced Lunch (SES) (poor, median, rich)	• Length of School Day in Minutes • Percentage of Students Eligible for Free or Reduced Lunch (SES)

The generally accepted statistical significance was measured at the .05 level to determine if the result was due to chance. The null hypothesis was rejected if the significance level indicated a (*p*-value) $\leq$ .05. Naturally, the researcher hoped to reject the null hypotheses.

The researcher used a regression analysis model to answer the research questions. The multiple regression equation was used to determine the correlation between the predictor variable, the length of the school day, with the dependent variable, 2011 HSPA scores. Initially, the researcher used a simultaneous regression method because Leech et al. (2011) recommends it " . . . if the researcher has no prior ideas about which variables will create the best prediction equation and has a reasonably small set of predictors" (p. 106). However, this method was followed by the hierarchical method which Leech et al. (2011) suggest to use "when one has an idea about the order in which one wants to enter predictors and wants to know how prediction by certain variables improves on prediction by others" (p. 106).

Research Questions

The overarching research question used in this study asks: What is the influence of length of school day on the Grade 11, 2011 New Jersey state-mandated High School Proficiency Assessment (HSPA) scores when controlling for student, school, and staff variables?

Research Question 1: What is the strength and direction of the relationship between length of school day on the Grade 11, 2011 New Jersey state-mandated High School Proficiency Assessment (HSPA scores) in Language Arts when controlling for student, school and staff variables?

Research Question 2: What is the strength and direction of the relationship between length of school day on Grade 11, 2011 New Jersey state-mandated High School Proficiency Assessment (HSPA scores) in Mathematics when controlling for student, school and staff variables?

Null Hypotheses

Null Hypothesis 1: No statistically significant relationship exists between length of school day and actual school score performance on the 2011, NJ HSPA for the 326 New Jersey high schools as measured by percentage Proficient or above.

Null Hypothesis 2: No statistically significant relationship exists between length of school day and the actual Language Arts school score performance on the 2011 NJ HSPA for the 326 New Jersey high schools as measured by percentage Proficient or above.

Null Hypothesis 3: No statistically significant relationship exists between length of school day and the actual Mathematics school score performance on the 2011 Grade 11 NJ HSPA for the 326 New Jersey high schools as measured by Proficient or above.

The Dependent Variable Instrumentation

Instrumentation for this study consisted of proficiency levels on scores for the Math and Language Arts sections of the 2011, NJ HSPA exam. Because the HSPA is a criterion assessment versus a norm-referenced assessment, there are no comparisons between students. The test was given to first-time Grade 11 NJ high school students and to Grade 12 students who did not pass the assessment in their eleventh year. The test measures mastery of the NJ Core Curriculum Content Standards (NJCCCS) in Math and Language arts. Test items for the NJ HSPA were developed and reviewed by state-level committees. New Jersey teachers participated in the committee process.

Measure Incorporated (MI) was the HSPA test contractor who managed the overall testing and scoring process. "MI's senior project manager works closely with the NJDOE throughout the hand-scoring process and oversees all aspects of the project, including monitoring reader performance (reader reliability and production rates), directing retraining efforts, and supervising the capture of scoring data" (NJDOE, 2006, p. 5).

The state monitors the progression of school districts in reaching AYP (adequate yearly progress) targets and holds districts accountable for failing to meet AYP targets. The NJDOE (2006) guide to HSPA assessment stated the exam's main purpose: "The HSPA is a state test given to students in the eleventh grade to measure whether they have gained the knowledge and skills identified in the Core Curriculum Content Standards" (p. 1) and tells parents that "the HSPA will help determine whether your child is making satisfactory progress toward mastering the skills he or she will need to graduate from high school" (p. 1). Furthermore, the NJDOE expects each school district to achieve progress toward the overall stated goal: to achieve 100% proficiency for all students by the year 2014. Finally, the state legislation of New Jersey passed a law (18A: 7C-6.2) in 1988 that requires all students who graduate from a public high school in New Jersey to demonstrate skill mastery in order " . . . to function politically, economically, and socially in a democratic society" (NJDOE, 2006, p. 1).

The NJ HSPA Spring 2011 Executive Summary (NJDOE, 2011) confirmed scoring: "For each demographic group, the number of students participating, the percentage of students at each proficiency level, and the mean scale score are reported in each content area. HSPA scores are reported as scale scores in each of the content areas" (p. 1). Scores ranged as follows (See Figure 2):

1. Partially Proficient/Not Pass (100-199)
2. Proficient/Pass (200-249)
3. Advanced Proficient/Pass (250-300)

Proficiency Bands: Source NJ DOE, 2009

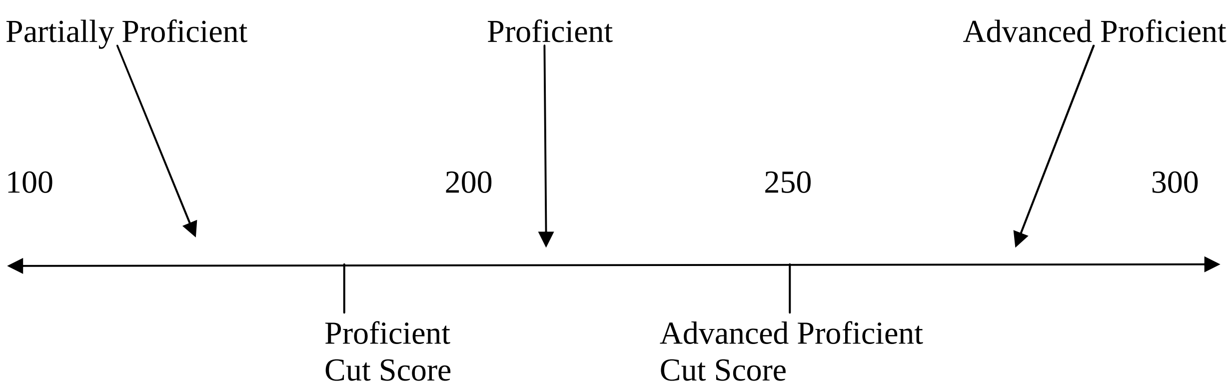


Figure 2. NJ HSPA Proficiency Bands

"Student scores included in the Partially Proficient level are considered to be below the state minimum of proficiency and these students may need additional instructional support, which could be in the form of individual or programmatic intervention" (NJDOE, 2009, p. 9).

Note that Koretz (2008) warns that “. . . proficient is merely an arbitrary point on a continuum of performance; it does not indicate mastery of all of a discrete set of skills” (p. 29).

Reliability and Validity

According to Koretz (2008):

> To get reliable information about which kids really have reached proficient status, one needs test items that discriminate well among kids whose mastery is near that level of proficiency and an even larger issue is deciding where to put the cut score that divides the failures from the ‘proficient’ successes (p. 29)

“Reliable scores show little inconsistency from one measurement to the next; that is, they contain relatively little measurement error (Koretz, 2008, p. 30). Further, Koretz (2008) confirms that validity is the “the single most important criterion for evaluating achievement testing.” (p. 31).

The NJDOE developed a model assessment system in order to review and modify the system as deemed necessary to assure all data points are accurately reported and recorded. The following constructs were devised to ensure reliability and validity:

- Alignment of assessments with valid and reliable existing state content standards.
- Assessments designed with valid and reliable controls built in, including highly trained readers for all open-ended items with quality controls such as read-behinds and, in most cases, double scoring—two cycles of reporting, as well as a mechanism for rescoring of tests when results are in question.
- Districts have the ability to validate the accuracy of demographic data on all students through a record change process.

- The scoring process entails an automatic adjudication of scoring on open-ended items for students whose scores are close but do not reach the proficiency level on each assessment. Districts may also ask for such adjudications at the time they receive Cycle I score reports.
- A 95% confidence interval calculated around the school or district's proficiency for all subgroups.
- 'Safe harbor' calculations applied to all students, as well as subgroup results, incorporating a 75% confidence interval in the determination.
- An appeal process implemented to guard against an error in the data or calculation at any step in the process (U.S. Department of Education, 2010).

CHAPTER IV

ANALYSIS OF THE DATA

Introduction

My purpose for this study was to explain the influence of length of school day for students, reported in minutes, who achieve proficiency or above on the Grade 11, 2011 NJ HSPA high school exit exam in Language Arts (LA) and Mathematics (MA). I have presented the results of my quantitative study on select staff, student, and school variables that were researched and examined in my literature review Chapter II and have been found to influence student performance. Furthermore, this chapter focuses on reporting the analysis and descriptive statistical results of the factors that were entered into the IBM SPSS version 22 (Statistical Package for the Social Sciences) predictive analytics software.

All data used for this study were archived, public information located on the NJDOE website. Because the data were available in the public domain, permission was not required for access. Each high school in this study was assigned a unique identifier code (school code, plus district code, plus county code) to ensure consistency and accuracy in transferring data files from the NJDOE website to a customized Excel workbook with two spreadsheets (one for MA and one for LA). Each row in the spreadsheet represented a different New Jersey high school. A column showing the total percentage of students passing (Proficient and Advanced Proficient) for each school in MA and LA was taken directly from the NJDOE database. Additional columns were added to calculate the percentage of students tested who were designated as part of each of the following demographic subcategories: economically disadvantaged, limited English proficiency, and students with disabilities. Each of these percentages were obtained by taking the total number of students in the particular subcategory who took the HSPA and then dividing that number by the total tested population for that school, and last multiplying the result by one hundred to obtain a percentage. (This calculation was performed because the NJDOE reports the percentages of students in these subcategories based on the total population by school as opposed to only those students tested in each school.)

I used a sample of 326 New Jersey public high schools in the analysis of MA HSPA scores and LA HSPA scores. Additionally, the sample included only those high schools in District Factor Grouping (DFG) A-J designated districts that housed enrollments of all four grade levels (9-12) and reported on all the independent staff, student, and school variables selected for this study. All charter, special services, special education, and vocational schools were eliminated from the study to ensure all results represented the most typical, comprehensive New Jersey public high schools.

Descriptive Statistics

Frequency Distributions

As background information, the frequency table (See Table 6) below displayed the average HSPA passing percentages separately for MA and LA by DFG group. As noted previously, in New Jersey the DFG categories denote the socioeconomic status (wealth) of a district with “A” districts representing the poorest communities and “J” districts representing the wealthiest locales. The unweighted average percentage of students passing the HSPA 2011for both MA and LA increased as the DFG group increased, with the greatest differences in passing percentages between the “A” and “B” DFG groups followed by the “B” and “CD” DFG groups. In addition, for each of the eight DFG groups the average passing percentage for LA was significantly higher than the average passing percentage for MA. The largest gap in the passing percentages between the two subjects was for the “A” DFG group and this gap decreased as the DFG group became closer to “J,” the wealthiest socio-economic group.

Table 6

Frequency Distribution Comparing the Average Percentage of Students Passing NJ HSPA 2011 by Schools Listed in DFG Groups A-J

Code	DFG	Number of NJ High Schools	LA Unweighted Average Percentage of Students Passing HSPA 2011	MA Unweighted Average Percentage of Students Passing HSPA 2011	Difference in Unweighted Averages Passing Percentages LA vs MA
1	A	52	72.7	46.8	25.9
2	B	36	84.6	63.2	21.4
3	CD	30	89.0	71.2	17.8
4	DE	51	92.1	76.2	15.9
5	FG	44	93.0	78.8	14.2
6	GH	54	95.1	84.8	10.3
7	I	47	96.9	89.3	7.6
8	J	12	97.4	93.3	4.1
Totals		326	89.4	73.9	15.5

A frequency distribution by DFG group illustrated the minimum to maximum school day lengths as well as the means and standard deviations for each group. A broad overview of the focused predictor variable studied (to determine the influence of the length of the school day on Grade 11 NJ HSPA scores) was shown in Table 7. The greatest spread in the length of the school day was for the “B” DFG group was followed by the “A” DFG group (these are the lowest socioeconomic designated schools).

Table 7

Frequency Distribution Comparing the School Day Length Minimum, Maximum, Mean and Standard Deviation by DFG Groups A-J

DFG	N	School Day Length Min.	School Day Length Max.	Mean	Std. Deviation
A	52	365	506	426.50	47.46
B	36	360	515	403.33	27.09
CD	30	372	435	403.77	17.21
DE	51	375	465	401.78	17.61
FG	44	375	465	406.50	20.37
GH	54	347	480	407.56	20.38
I	47	377	450	418.19	17.39
J	12	396	437	417.25	12.24

In Table 8 all the names of each variable appearing in SPSS charts and tables are listed.

Table 8

Variable Legend: Abbreviated Variable Names

DEPENDENT VARIABLE	SPSS MODEL LABEL
2011 HSPA PASSING SCORE (UNTRANSFORMED)	TP+AP
2011 HSPA MA TRANSFORMED PASSING SCORE	TPReflect
2011 HSPA LA TRANSFORMED PASSING SCORE	TPLA_Reflext
INDEPENDENT VARIABLES	SPSS MODEL LABEL
Staff Variables	
Faculty Attendance Rate	FATTEND
Faculty Mobility Rate	FMOBILITY
Percentage of Staff with Master's Degrees or Higher	MA+
Student Variables	
Student Attendance Rate	G11attend
Student Mobility Rate	STMOB
Percentage of Students Eligible for Free or Reduced Lunch	SES
Percentage of Students with Disabilities	DIS
Percentage of Students with Limited English	LEP
School Variables	
Length of the School Day	SCHDAYL
School Size	enrG9to12

Before determining which staff, student, and school variables revealed a statistically significant relationship to student achievement, as measured by the dependent variable TP+AP for NJ HSPA Grade 11, 2011 scores, the distribution of the HPSA passing scores were checked for normality separately for MA and LA in SPSS.

HSPA Math (MA) Scores

Tests of Normality Dependent Variable MA

Tests for normality, on the sampling distribution (326 schools) were conducted on the dependent variable (TP+AP) by using the Explore command in SPSS. The MA scores (TP+AP) revealed an asymmetrical distribution with a significant negative, left skew as shown below in Figure 3. "If a distribution has values of skew or kurtosis above or below 0, then this indicates a deviation from normal" (Field, 2013, p. 21). However, Field (2013) disclosed that "from the central limit theorem, in large samples (n > 30), the sampling distribution tends to be normal, regardless of the shape of the data in the sample" (p. 871). Additionally, Field (2013) contended the following:

1. the assumption of normality tends to get translated as 'your data need to be normally distributed,' even though that's not really what it means"
2. although it is often the shape of the sample distribution that matters, researchers tend to look at the scores on the outcome variable (or residuals) when assessing normality (p. 169)

Furthermore, "the central limit theorem means that there are a variety of situations in which we can assume normality regardless of the shape of our sample data" (Lumley, Diehr, Emerson, & Chen, 2002, as cited by Field, 2013, p. 170).

Nevertheless (See Figure 3), "histograms and descriptive statistics are a good way of getting an instant picture of the distribution of your data" (Field, 2009, p. 4).

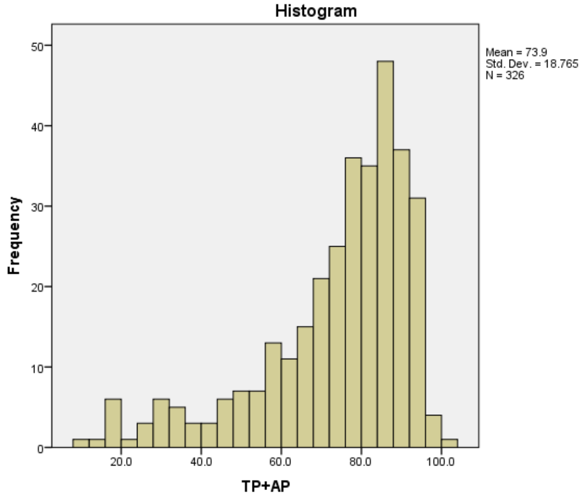


Figure 3. MA HSPA Normality Test Distribution Histogram Untransformed Dependent Variable (TP+AP)

To further explore the degree of negative skewness of the MA dependent variable (TP+AP), the normality of the data was assessed by calculating skewness and kurtosis statistics. For the HSPA MA scores in Table 9, the z-score of skewness -1.351/.135 = -10.01; (the z-scores are significant at $p < .05$ because they lie outside the -1.96 and 1.96 range (Field, 2013, p. 179). The interpretation of deviations of skew and kurtosis based on z-scores was $z < 1.96$, which indicated the distribution of the MA passing percentages (TP+AP) were significantly negatively skewed. Similarly found was a kurtosis z-score of 1.368/.269 = 5.09. Because the z-score was > 1.96, this denoted that the distribution of the MA scores had significant positive kurtosis. Both the significant skewness and kurtosis suggested a non-normal distribution. All data were re-verified to assure that all numbers were entered correctly into the data set from the NJDOE site.

Table 9

MA Descriptives Untransformed Dependent Variable (TP+AP)

			Statistic	Std. Error
TP+AP	Mean		73.903	1.0393
	95% Confidence Interval for Mean	Lower Bound	71.858	
		Upper Bound	75.947	
	5% Trimmed Mean		75.597	
	Median		79.350	
	Variance		352.139	
	Std. Deviation		18.7654	
	Minimum		10.7	
	Maximum		100.0	
	Range		89.3	
	Interquartile Range		22.1	
	Skewness		-1.351	.135
	Kurtosis		1.368	.269

Tests of normality of the distribution were further supported by the Kolmogorov-Smirnov (K-S) and Shapiro-Wilk (S-W) tests (See Table 10). Both tests revealed statistically significant results: for K-S, D(326) = .15, $p = .001 < .05$ and S-W, W(326) = .87, $p = .001 < .05$.

Table 10

MA Tests of Normality Untransformed Dependent Variable

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.
TP+AP	.153	326	.000	.868	326	.000

a. Lilliefors Significance Correction

To correct negatively skewed data, Field (2009, p. 155) advised that you first reverse the scores (subtracting each score from the highest score in the data set +1); in this data set the number 101 was subtracted from each HSPA MA passing score (TP+AP). As a second step, to correct a negative skew, Field (2009, p. 155) recommended running a transformation in SPSS. In this analysis the researcher used a logarithm transformation (log10) in SPSS and converted the dependent variable into a more symmetrical distribution; the final transformed distribution of passing scores was labeled TPReflect. The TPReflect histogram (Figure 4) became much less skewed than the original TP+AP distribution but the distribution of transformed scores still had a slight left (negative skew).

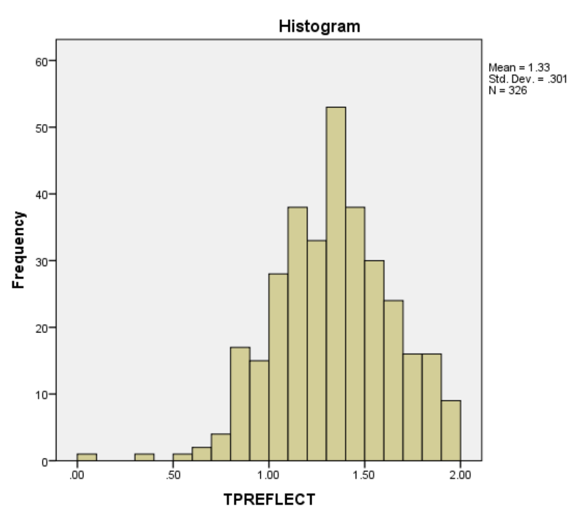


Figure 4. MA HSPA Distribution Histogram Transformed Dependent Variable (TPReflect)

The descriptive statistics for TPReflect exposed the improved skewness statistic (See Table 11); skewness z-score = -.302 / .135 = -2.24 and kurtosis z-score = .663 / .269 = 2.46. While both these z-scores were statistically significant (since they fall outside of the -1.96 and 1.96 range), they are far less extreme than the non-transformed data; however, Field (2008) states the following:

> An absolute value greater than 1.96 is significant at p <.05, above 2.58 is significant at p < .01, and absolute values above about 3.29 are significant at p < .001. Large samples will give rise to small standard errors and so when sample sizes are big, significant values arise from even small deviations from normality. In most samples it's Ok to look for values above 1.96; however, in large samples this criterion should be increased to 2.58 or 3.29; and in very large samples, because of the problem of small standard errors that I've described, no criterion should be applied to all! (p. 7).
>
> The important value of a z is 1.96 because this cuts off the top 2.5% of the distribution, and its counterpart at the opposite end (-1.96) cuts off the bottom 2.5% of the distribution. As such, taken together, this value cuts off 5% of scores, or put another way, 95% of z-scores lie between -1.96 and 1.96. The two important benchmarks are +2.58 and +3.29, which cut off 1% of scores, respectively. Put another way, 99% of z-scores lie between -2.58 and 2.58, and 99.9% of them lie between -3.29 and 3.29 (Field, 2013, p. 180).

Table 11

MA Descriptives Tranformed Dependent Variable (TPReflect)

			Statistic	Std. Error
TPREFLECT	Mean		1.3348	.01669
	95% Confidence Interval for Mean	Lower Bound	1.3020	
		Upper Bound	1.3676	
	5% Trimmed Mean		1.3388	
	Median		1.3355	
	Variance		.091	
	Std. Deviation		.30133	
	Minimum		.00	
	Maximum		1.96	
	Range		1.96	
	Interquartile Range		.42	
	Skewness		-.302	.135
	Kurtosis		.663	.269

The tests of normality on the transformed data (TPReflect) for K-S was not significant (See Table 12) D(326) = .03, p = .200 >.05, but the S-W test was significant W(326) = .99, p = .002 <.05. Nevertheless, because my sample size of 326 schools was less than 2,000, the S-W was the preferred test statistic for normality. Since the transformed dependent variable (TPReflect) represented a much closer to normal distribution than the untransformed dependent variable (TP+AP) and the fact that the sample size of 326 schools was relatively large, the transformed variable (TPReflect) was chosen and used in subsequent regression analysis.

Table 12

MA Tests of Normality Transformed Dependent Variable (TPReflect)

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
TPREFLECT	.026	326	.200*	.985	326	.002

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Simultaneous Regression MA

The first analysis run in SPSS was a regression using the enter method that included all the selected independent variables obtained from 2011 NJ School Report Card Data. The purpose of this regression was to determine and show which variables had a significant influence on the HSPA passing percentages as well as to identify potential mulitcollinearity issues between predictor variables. Predictor variables found to be strongly related (those with a Pearson Linear Correlation Coefficient (*r*) of $r > .60$ or $r < -.60$) informed the research of potential multicollinearity issues within the regression model. The results of the means and standard deviations were captured in Table 13 of the dependent (TPReflect) and the independent variables.

Table 13

MA Descriptive Statistics Simultaneous Multiple Regression Transformed Dependent Variable (TPReflect)

	Mean	Std. Deviation	N
TPREFLECT	1.3348	.30133	326
SCHDAYL	410.742	27.4352	326
STMOB	9.579	11.2019	326
SES	26.946	27.2800	326
LEP	.666	2.4382	326
DIS	1.343	4.0715	326
FATTEND	95.633	7.7370	326
FMOBILITY	4.313	5.4614	326
MA+	51.830	14.0925	326
enrG9to12	1095.531	599.7438	326
G11attend	93.372	3.2624	326

The correlation matrix (See Table 14) presented the Pearson correlation coefficient r between each pair of variables including the independent variable; also depicted was the statistical significance (*p*-value) of each correlation coefficient. Among the possible pairs of independent variables, the strongest, statistically significant correlations were between G11attend and STMOB (r = -.67, p=.0001 <.05) and between LEP and DIS (r=.80, p=.0001 <.05).

Table 14

MA Correlations of Simultaneous Multiple Regression Transformed Dependent Variable (TPReflect)

		TPREFLECT	SCHDAYL	STMOB	SES	LEP	DIS	FATTEND	FMOBILITY	MA+	enrG9to12	G11attend
Pearson Correlation	TPREFLECT	1.000	-.156	.567	.657	.139	.123	-.210	.133	-.387	-.157	-.601
	SCHDAYL	-.156	1.000	-.044	.196	.050	.016	.121	.095	.078	-.070	.054
	STMOB	.567	-.044	1.000	.521	.040	.008	-.023	.228	-.313	-.219	-.670
	SES	.657	.196	.521	1.000	.209	.142	-.147	.199	-.353	-.177	-.518
	LEP	.139	.050	.040	.209	1.000	.804	.004	-.017	.031	.277	-.111
	DIS	.123	.016	.008	.142	.804	1.000	.019	-.005	.026	.391	-.058
	FATTEND	-.210	.121	-.023	-.147	.004	.019	1.000	.016	.022	.050	.367
	FMOBILITY	.133	.095	.228	.199	-.017	-.005	.016	1.000	-.081	-.121	-.296
	MA+	-.387	.078	-.313	-.353	.031	.026	.022	-.081	1.000	.098	.261
	enrG9to12	-.157	-.070	-.219	-.177	.277	.391	.050	-.121	.098	1.000	.143
	G11attend	-.601	.054	-.670	-.518	-.111	-.058	.367	-.296	.261	.143	1.000
Sig. (1-tailed)	TPREFLECT	.	.002	.000	.000	.006	.013	.000	.008	.000	.002	.000
	SCHDAYL	.002	.	.214	.000	.185	.384	.014	.044	.079	.104	.167
	STMOB	.000	.214	.	.000	.233	.444	.342	.000	.000	.000	.000
	SES	.000	.000	.000	.	.000	.005	.004	.000	.000	.001	.000
	LEP	.006	.185	.233	.000	.	.000	.470	.378	.288	.000	.023
	DIS	.013	.384	.444	.005	.000	.	.363	.468	.320	.000	.146
	FATTEND	.000	.014	.342	.004	.470	.363	.	.383	.348	.185	.000
	FMOBILITY	.008	.044	.000	.000	.378	.468	.383	.	.072	.015	.000
	MA+	.000	.079	.000	.000	.288	.320	.348	.072	.	.039	.000
	enrG9to12	.002	.104	.000	.001	.000	.000	.185	.015	.039	.	.005
	G11attend	.000	.167	.000	.000	.023	.146	.000	.000	.000	.005	.
N	TPREFLECT	326	326	326	326	326	326	326	326	326	326	326
	SCHDAYL	326	326	326	326	326	326	326	326	326	326	326
	STMOB	326	326	326	326	326	326	326	326	326	326	326
	SES	326	326	326	326	326	326	326	326	326	326	326
	LEP	326	326	326	326	326	326	326	326	326	326	326
	DIS	326	326	326	326	326	326	326	326	326	326	326
	FATTEND	326	326	326	326	326	326	326	326	326	326	326
	FMOBILITY	326	326	326	326	326	326	326	326	326	326	326
	MA+	326	326	326	326	326	326	326	326	326	326	326
	enrG9to12	326	326	326	326	326	326	326	326	326	326	326
	G11attend	326	326	326	326	326	326	326	326	326	326	326

The ANOVA reported in Table 15 confirmed that the overall model's regression was significant $F(10, 315) = 48.46$, $p < .0001$.

Table 15

MA ANOVA[a] All Variables Transformed Dependent Variable (TPReflect)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17.884	10	1.788	48.461	.000[b]
	Residual	11.625	315	.037		
	Total	29.509	325			

a. Dependent Variable: TPREFLECT

b. Predictors: (Constant), G11attend, SCHDAYL, DIS, MA+, FMOBILITY, FATTEND, enrG9to12, SES, STMOB, LEP

The model summary illustrated in Table 16 had an adjusted R square (R^2) of 59% which indicated that 59% of the variance in the dependent variable is explained by the model (e.g., by the variations in the predictor variables). The Durbin-Watson statistic at 1.775 showed no significant auto correlation in the corresponding residuals.

Table 16

MA Model Summary[b] All Variables Transformed Dependent Variable (TPReflect)

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.778[a]	.606	.594	.19211	.606	48.461	10	315	.000	1.775

a. Predictors: (Constant), G11attend, SCHDAYL, DIS, MA+, FMOBILITY, FATTEND, enrG9to12, SES, STMOB, LEP

b. Dependent Variable: TPREFLECT

The Coefficients (See Table 17) showed that the independent variables SCHDAYL, STMOB, SES, MA+ and G11Attend all had a significant influence on the dependent variable (TPReflect); the *p*-values associated with these variables are < .05. The standardized Beta (β) shows the strength and direction of the relationship between the given independent variable and dependent variable. Because TPReflect is a transformed dependent variable (it involved a reversal of the original dependent variable scores), independent variables with positive β's actually had a negative influence on the original TP+AP dependent variable (HSPA passing percentages). Similarly, independent variables with negative β's had a positive influence on the dependent variable.

The variables with the greatest to least significance with positive influence were G11attend, SCHDAYL, MA+, FMOBILTY, enrG9-12, LEP, and FAttend; alternatively, the negative influencers in the order of most to least significant were SES, STMOB, and DIS. Caution should be exercised when interpreting the β values associated with independent variables that are highly correlated with other independent variables in the model, including STMOB, G11attend, LEP and DIS.

The Tolerance and VIF collinearity statistics in the model provided further substantiation of predictor variables that were highly correlated with other independent variables. A VIF statistic >2 indicated a high correlation for STMOB (2.309), LEP (2.960), DIS (3.115), and G11attend (2.627).

Table 17

MA Coefficients[a] All Variables with Transformed Dependent Variable (TPReflect)

		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	4.395	.473		9.295	.000					
	SCHDAYL	-.002	.000	-.217	-5.747	.000	-.156	-.308	-.203	.875	1.143
	STMOB	.003	.001	.125	2.331	.020	.567	.130	.082	.433	2.309
	SES	.005	.001	.469	9.787	.000	.657	.483	.346	.545	1.836
	LEP	-.006	.008	-.051	-.837	.403	.139	-.047	-.030	.338	2.960
	DIS	.008	.005	.109	1.752	.081	.123	.098	.062	.321	3.115
	FATTEND	-.001	.002	-.022	-.542	.588	-.210	-.031	-.019	.739	1.353
	FMOBILITY	-.003	.002	-.052	-1.386	.167	.133	-.078	-.049	.874	1.144
	MA+	-.002	.001	-.104	-2.672	.008	-.387	-.149	-.094	.824	1.214
	enrG9to12	-2.600E-5	.000	-.052	-1.284	.200	-.157	-.072	-.045	.770	1.299
	G11attend	-.022	.005	-.234	-4.085	.000	-.601	-.224	-.144	.381	2.627

a. Dependent Variable: TPREFLECT

Using the backward method, a second multiple regression analysis was run in SPSS (See Table 18). Before actually running this model, two of the independent variables (STMOB and LEP) were removed (as previously explained) to eliminate any multicollinareity issues. Except for STMOB and LEP, all the independent significant variables were entered. The significance of each independent variable was verified, and the variable with the least significance with the highest *p*-value was noted.

Table 18

MA Descriptive Statistics (second multiple regression backward method) with Selected Variables and Transformed Dependent Variable (TPReflect)

	Mean	Std. Deviation	N
TPREFLECT	1.3348	.30133	326
SES	26.946	27.2800	326
G11attend	93.372	3.2624	326
SCHDAYL	410.742	27.4352	326
MA+	51.830	14.0925	326
DIS	1.343	4.0715	326

The results from the ANOVA (See Table 19) suggested that although all the regression models were significant, Model 4 contained the following independent variables: SES, G11attend, SCHDAYL, and MA+. The regression statistics for Model 4 is $F(4, 321) = 116.109$, $p = .001 < .05$.

Table 19

MA ANOVA[a] Selected Variables (second MR) with Transformed Dependent Variable (TPReflect)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12.719	1	12.719	245.428	.000[b]
	Residual	16.791	324	.052		
	Total	29.509	325			
2	Regression	15.457	2	7.728	177.638	.000[c]
	Residual	14.053	323	.044		
	Total	29.509	325			
3	Regression	17.136	3	5.712	148.645	.000[d]
	Residual	12.373	322	.038		
	Total	29.509	325			
4	Regression	17.449	4	4.362	116.109	.000[e]
	Residual	12.060	321	.038		
	Total	29.509	325			
5	Regression	17.498	5	3.500	93.234	.000[f]
	Residual	12.011	320	.038		
	Total	29.509	325			

a. Dependent Variable: TPREFLECT
b. Predictors: (Constant), SES
c. Predictors: (Constant), SES, G11attend
d. Predictors: (Constant), SES, G11attend, SCHDAYL
e. Predictors: (Constant), SES, G11attend, SCHDAYL, MA+
f. Predictors: (Constant), SES, G11attend, SCHDAYL, MA+, DIS

The results from the Model Summary (See Table 20) highlighted that Model 5's adjusted R^2 of 58.6 %, meaning that 58.6% variation in the dependent variable (TPReflect) can be explained by this model. An examination of the model further showed that the elimination of the non-significant variables had little effect on the predictive power of the model (the change in R^2 went from .588 to .586). The fact that the Durbin-Watson statistic of 1.741 was close to 2 indicated that no significant auto correlations in the residuals produced by the model exist.

Table 20

MA Model Summary[f] Selected Variables (second MR) with Transformed Dependent Variable (TPReflect)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.657[a]	.431	.429	.22765	.431	245.428	1	324	.000	
2	.724[b]	.524	.521	.20858	.093	62.934	1	323	.000	
3	.762[c]	.581	.577	.19603	.057	43.696	1	322	.000	
4	.769[d]	.591	.586	.19383	.011	8.338	1	321	.004	
5	.770[e]	.593	.587	.19374	.002	1.299	1	320	.255	1.730

a. Predictors: (Constant), SES
b. Predictors: (Constant), SES, G11attend
c. Predictors: (Constant), SES, G11attend, SCHDAYL
d. Predictors: (Constant), SES, G11attend, SCHDAYL, MA+
e. Predictors: (Constant), SES, G11attend, SCHDAYL, MA+, DIS
f. Dependent Variable: TPREFLECT

The coefficients (See Table 21) signaled that all four independent variables (in the final model, 5) were significant and had *p*-values of < .05. In addition, SCHDAYL, G11attend and MA+ had negative standardized beta values, indicating that these variables had a positive relationship with the original dependent variable (TP+AP). By comparison, SES had a standardized positive beta value of .510, indicating that this variable had a negative influence on the MA passing percentage (TP+AP). In summary, independent variables in order of influence on the dependent variable were SES (beta .510), G11attend (-.295), SCHDAYL (-.232), and MA+ (-.112).

The fact that the VIF (variance inflation factor) figures for each of the independent variables were less than 2 confirmed that this final model had no multicollinearity issues.

Table 21

MA Coefficients[a] Selected Variables (second MR) with Transformed Dependent Variable (TPReflect)

		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	5.023	.388		12.963	.000					
	SCHDAYL	-.003	.000	-.229	-6.057	.000	-.156	-.322	-.216	.888	1.126
	SES	.005	.001	.492	10.628	.000	.657	.513	.378	.592	1.688
	DIS	.005	.003	.066	1.652	.100	.123	.092	.059	.795	1.258
	FATTEND	.000	.002	.009	.218	.827	-.210	.012	.008	.832	1.202
	FMOBILITY	-.003	.002	-.052	-1.358	.175	.133	-.076	-.048	.880	1.137
	MA+	-.002	.001	-.115	-2.942	.003	-.387	-.163	-.105	.835	1.197
	enrG9to12	-3.153E-5	.000	-.063	-1.560	.120	-.157	-.087	-.056	.784	1.276
	G11attend	-.029	.004	-.309	-6.608	.000	-.601	-.348	-.235	.579	1.727
2	(Constant)	5.021	.387		12.981	.000					
	SCHDAYL	-.003	.000	-.228	-6.074	.000	-.156	-.322	-.216	.897	1.115
	SES	.005	.001	.492	10.642	.000	.657	.512	.378	.592	1.688
	DIS	.005	.003	.066	1.666	.097	.123	.093	.059	.797	1.255
	FMOBILITY	-.003	.002	-.050	-1.343	.180	.133	-.075	-.048	.895	1.118
	MA+	-.002	.001	-.115	-2.979	.003	-.387	-.165	-.106	.842	1.187
	enrG9to12	-3.153E-5	.000	-.063	-1.563	.119	-.157	-.087	-.056	.784	1.276
	G11attend	-.028	.004	-.306	-6.981	.000	-.601	-.365	-.248	.659	1.517
3	(Constant)	4.909	.378		12.983	.000					
	SCHDAYL	-.003	.000	-.233	-6.234	.000	-.156	-.330	-.222	.906	1.104
	SES	.005	.001	.491	10.608	.000	.657	.511	.378	.593	1.687
	DIS	.005	.003	.066	1.661	.098	.123	.093	.059	.797	1.255
	MA+	-.002	.001	-.115	-2.973	.003	-.387	-.164	-.106	.842	1.187
	enrG9to12	-2.973E-5	.000	-.059	-1.475	.141	-.157	-.082	-.053	.787	1.270
	G11attend	-.027	.004	-.292	-6.850	.000	-.601	-.358	-.244	.700	1.429
4	(Constant)	4.900	.379		12.937	.000					
	SCHDAYL	-.003	.000	-.231	-6.161	.000	-.156	-.326	-.220	.908	1.101
	SES	.006	.001	.502	10.983	.000	.657	.523	.392	.609	1.641
	DIS	.003	.003	.041	1.140	.255	.123	.064	.041	.973	1.028
	MA+	-.002	.001	-.116	-2.974	.003	-.387	-.164	-.106	.842	1.187
	G11attend	-.027	.004	-.296	-6.951	.000	-.601	-.362	-.248	.703	1.423
5	(Constant)	4.897	.379		12.924	.000					
	SCHDAYL	-.003	.000	-.232	-6.191	.000	-.156	-.327	-.221	.909	1.100
	SES	.006	.000	.510	11.273	.000	.657	.533	.402	.623	1.605
	MA+	-.002	.001	-.112	-2.888	.004	-.387	-.159	-.103	.848	1.179
	G11attend	-.027	.004	-.295	-6.932	.000	-.601	-.361	-.247	.703	1.422

a. Dependent Variable: TPREFLECT

Hierarchical Regression MA

A hierarchical regression was run using the four significant variables obtained in the final model of the backwards regression (See Table 22). Each variable was entered one by one based on the magnitudes of their betas, with the largest beta having been entered first. Note that the independent variable of DIS was arbitrarily included in this final model (even though this variable was not statistically significant). The decision to include this variable was due to the fact that the variable DIS had moderate significance (p = .083) in the first iteration of the SPSS backward model. The percentage of students with disabilities (DIS) is often associated with a school's HSPA performance.

Table 22

MA Descriptive Statistics Hierarchical Regression Selected Variables with Transformed Dependent Variable (TPReflect)

	Mean	Std. Deviation	N
TPREFLECT	1.3348	.30133	326
SES	26.946	27.2800	326
G11attend	93.372	3.2624	326
SCHDAYL	410.742	27.4352	326
MA+	51.830	14.0925	326
DIS	1.343	4.0715	326

The results from the ANOVA (See Table 23) revealed that each of the five iterations of the hierarchical model were statistically significant, with the final model having the following statistics $F(5, 320) = 93.23$, $p = .001 < .05$.

Table 23

MA ANOVA[a] for Hierarchical Regression for Selected Variables with Transformed Dependent Variable (TPReflect)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12.719	1	12.719	245.428	.000[b]
	Residual	16.791	324	.052		
	Total	29.509	325			
2	Regression	15.457	2	7.728	177.638	.000[c]
	Residual	14.053	323	.044		
	Total	29.509	325			
3	Regression	17.136	3	5.712	148.645	.000[d]
	Residual	12.373	322	.038		
	Total	29.509	325			
4	Regression	17.449	4	4.362	116.109	.000[e]
	Residual	12.060	321	.038		
	Total	29.509	325			
5	Regression	17.498	5	3.500	93.234	.000[f]
	Residual	12.011	320	.038		
	Total	29.509	325			

a. Dependent Variable: TPREFLECT

b. Predictors: (Constant), SES

c. Predictors: (Constant), SES, G11attend

d. Predictors: (Constant), SES, G11attend, SCHDAYL

e. Predictors: (Constant), SES, G11attend, SCHDAYL, MA+

f. Predictors: (Constant), SES, G11attend, SCHDAYL, MA+, DIS

The Model Summary (See Table 24) demonstrated that Model 5's adjusted R^2 was 58.7 %; therefore, 58.7% of the variation in the dependent variable (TPReflect, HSPA MA scores) can be explained by this model. The R^2 change column showed the contributions of each independent variable on the predictive capability of the model. SES contributes 43.1% to the predictive power of the model, while G11attend contributed 9.3%, SCHDAYL contributed 5.7%, MA+ contributed 1.1%, and DIS contributed .2%.

The fact that the Durbin Watson statistic of 1.73 was close to 2 indicated that no significant auto correlations in the residuals were produced by the model. Regarding the Durbin-Watson statistic, it "can vary between 0 and 4, with a value of 2, meaning that the residuals are uncorrelated" (Field, 2013, p. 874).

Table 24

MA Model Summary[f] Hierarchical Regression with Transformed Dependent Variable (TPReflect)

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.657[a]	.431	.429	.22765	.431	245.428	1	324	.000	
2	.724[b]	.524	.521	.20858	.093	62.934	1	323	.000	
3	.762[c]	.581	.577	.19603	.057	43.696	1	322	.000	
4	.769[d]	.591	.586	.19383	.011	8.338	1	321	.004	
5	.770[e]	.593	.587	.19374	.002	1.299	1	320	.255	1.730

a. Predictors: (Constant), SES

b. Predictors: (Constant), SES, G11attend

c. Predictors: (Constant), SES, G11attend, SCHDAYL

d. Predictors: (Constant), SES, G11attend, SCHDAYL, MA+

e. Predictors: (Constant), SES, G11attend, SCHDAYL, MA+, DIS

f. Dependent Variable: TPREFLECT

The Coefficients (See Table 25) illustrated that in the fifth hierarchical model, G11attend, SCHDAYL, MA+ had positive influences on the original dependent variable as evidenced by their negative betas, while SES and DIS had a negative impact on the HSPA passing percentages because these variables had positive betas. Note that the DIS variable was not statistically significant *p*-value = .255 is > .05. The fact that the VIF's for all five independent variables were < 2 signified that no multicollinearity issues existed in the model.

Table 25

MA Coefficients[a] on Hierarchical Regression Model with Transformed Dependent Variable (TPReflect)

		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.139	.018		64.244	.000					
	SES	.007	.000	.657	15.666	.000	.657	.657	.657	1.000	1.000
2	(Constant)	4.266	.394		10.815	.000					
	SES	.005	.000	.472	10.514	.000	.657	.505	.404	.732	1.367
	G11attend	-.033	.004	-.356	-7.933	.000	-.601	-.404	-.305	.732	1.367
3	(Constant)	4.907	.383		12.806	.000					
	SES	.006	.000	.548	12.528	.000	.657	.572	.452	.681	1.468
	G11attend	-.028	.004	-.304	-7.072	.000	-.601	-.367	-.255	.706	1.415
	SCHDAYL	-.003	.000	-.248	-6.610	.000	-.156	-.346	-.239	.929	1.077
4	(Constant)	4.897	.379		12.924	.000					
	SES	.006	.000	.510	11.273	.000	.657	.533	.402	.623	1.605
	G11attend	-.027	.004	-.295	-6.932	.000	-.601	-.361	-.247	.703	1.422
	SCHDAYL	-.003	.000	-.232	-6.191	.000	-.156	-.327	-.221	.909	1.100
	MA+	-.002	.001	-.112	-2.888	.004	-.387	-.159	-.103	.848	1.179
5	(Constant)	4.900	.379		12.937	.000					
	SES	.006	.001	.502	10.983	.000	.657	.523	.392	.609	1.641
	G11attend	-.027	.004	-.296	-6.951	.000	-.601	-.362	-.248	.703	1.423
	SCHDAYL	-.003	.000	-.231	-6.161	.000	-.156	-.326	-.220	.908	1.101
	MA+	-.002	.001	-.116	-2.974	.003	-.387	-.164	-.106	.842	1.187
	DIS	.003	.003	.041	1.140	.255	.123	.064	.041	.973	1.028

a. Dependent Variable: TPREFLECT

Univariate Analysis Transformed Dependent Variable MA

A Univariate Analysis of Variance was performed to secure a better understanding of the impact of the two most significant independent variables (SES and SCHDAYL) on the HSPA MA passing percentage, when controlling for G11attend (See Table 26). The dependent variable used in this ANOVA was the transformed dependent variable (TPReflect). Two sets of grouping variables were created. For SES, the schools were grouped into three, approximately equal-sized bins and labeled rich, median, and poor (based on the percentage of SES students). Similarly, for SCHDAYL the schools were grouped into three equal-sized bins (labeled short, median and long) based on the length of school day reported by the NJDOE. The number of schools included in each grouping bin (SCHDAYL and SES) can be seen below.

Table 26

MA Univariate Analysis of Variance Between-Subject Factors with Transformed Dependent Variable (TPReflect) and Binned SCHDAYL and SES

		Value Label	N
SCHDAYL (Binned)	1	Short	115
	2	Med	112
	3	Long	99
SES (Binned)	1	rich	109
	2	med	109
	3	poor	108

In the tests between-subjects effects (See Table 27) were the results of the factorial ANOVA analysis performed on the binned data previously explained and shown above; significant differences in the dependent variable (TPReflect) between the SES bins F (2, 317) = 127.92, p = .0001 <.05 as well as between the SCHDAYL bins F (2, 317) = 7.41, p = .0001 <.05 were found. However, no significant interaction between the SES bins and the SCHDAYL bins on the dependent variable (TPReflect) were reflected; the interaction statistics were F(4, 317) = .85, p = .496 >.05.

Table 27

MA Univariate Analysis of Variance Tests of Between-Subjects Effects with Transformed Variable (TPReflect) and Binned Factors

Dependent Variable: TPREFLECT

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	14.103[a]	8	1.763	36.272	.000
Intercept	557.804	1	557.804	11477.208	.000
Schoolbin	.720	2	.360	7.411	.001
Sesbin	12.434	2	6.217	127.922	.000
schoolbin * sesbin	.165	4	.041	.848	.496
Error	15.407	317	.049		
Total	610.329	326			
Corrected Total	29.509	325			

a. R Squared = .478 (Adjusted R Squared = .465)

Post Hoc Tests MA

A Tukey HSD post hoc test (multiple comparisons on SCHDAYL) was performed in order to determine the exact differences between the binned groups (See Table 28). For the SCHDAYL groups, significant differences in the transformed dependent variable (TPReflect) were found between the short and median bins and the short and long bins; however, no significant differences were found in the dependent variable between the median and long binned schools. Because we used the transformed variable (that involved a reversal), the fact that the differences in the dependent variable between the median and short bins was negative indicated that schools that had a median length day performed better than schools that had a shorter day. The mean difference between the long and short schools was negative and therefore the schools that had a longer school day performed better on the HSPA MA than the schools that had a shorter day.

Table 28

MA Tukey HSD Post Hoc Multiple Comparisons SCHDAYL Bin with Transformed Dependent Variable (TPReflect)

Tukey HSD

(I) SCHDAYL (Binned)	(J) SCHDAYL (Binned)	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Short	Med	.1241*	.02927	.000	.0552	.1930
	Long	.1521*	.03022	.000	.0809	.2232
Med	Short	-.1241*	.02927	.000	-.1930	-.0552
	Long	.0279	.03041	.629	-.0437	.0996
Long	Short	-.1521*	.03022	.000	-.2232	-.0809
	Med	-.0279	.03041	.629	-.0996	.0437

Based on observed means.

The error term is Mean Square(Error) = .049.

* The mean difference is significant at the 0.05 level.

A Tukey HSD post hoc test (multiple comparisons) was run on the SES binned groups (See Table 29). The post hoc showed that there were significant differences between (a) rich and median districts, (b) rich and poor districts, and (c) median and poor districts. The fact that the dependent variable (TPReflect) was a transformed variable (which involved a reversal of scores) illustrated the difference in the dependent variable between rich and median schools as negative and that indicated that rich schools performed better on the HSPA MA than median schools. Similarly, the fact that the difference between rich and poor schools was negative reflected that rich districts performed better on the HSPA MA than poor districts. Finally, the difference between median and poor districts was also negative, which meant that schools with median status performed better on the HSPA MA than schools with poorer students.

Table 29

MA Tukey HSD Post Hoc Multiple Comparisons SES Bin with Transformed Dependent Variable (TPReflect)

Tukey HSD

(I) SES (Binned)	(J) SES (Binned)	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Rich	med	-.2470*	.02986	.000	-.3173	-.1767
	poor	-.4920*	.02993	.000	-.5624	-.4215
Med	rich	.2470*	.02986	.000	.1767	.3173
	poor	-.2450*	.02993	.000	-.3154	-.1745
Poor	rich	.4920*	.02993	.000	.4215	.5624
	med	.2450*	.02993	.000	.1745	.3154

Based on observed means.

The error term is Mean Square(Error) = .049.

* The mean difference is significant at the 0.05 level.

The following chart (See Figure 5) depicted the plots of the estimated marginal means for the dependent variable, TPReflect, for the SCHDAYL and was shown separately by SES bin. The line segments for the poor, median, and rich schools were separate and distinct, which clearly illustrated significant differences in HSPA MA performance between the three types of schools (poor, median, rich). Because the transformation of the dependent variable, TPReflect, involved a reversal of the scores, the order in which the line segments appeared on the graph clearly illuminated that the poor schools performed significantly lower than the median schools and that the median schools performed significantly worse than the wealthier schools on the HSPA MA. For the poor schools (and to a lesser extent the wealthier schools) the lines sloped downward. Because the dependent variable, TPReflect, involved a reversal of scores, this meant that HSPA MA test performance improved for poor schools as the school day grew longer (from a short to median length as well as when it increased from a median to a long length). The same was true for the wealthy SES binned schools. Nevertheless, although the schools in the median

SES bin showed some improvement in MA test performance when the school day was increased from a short day to a median length school day, there was virtually no change in performance when the school day went from median length to a long day.

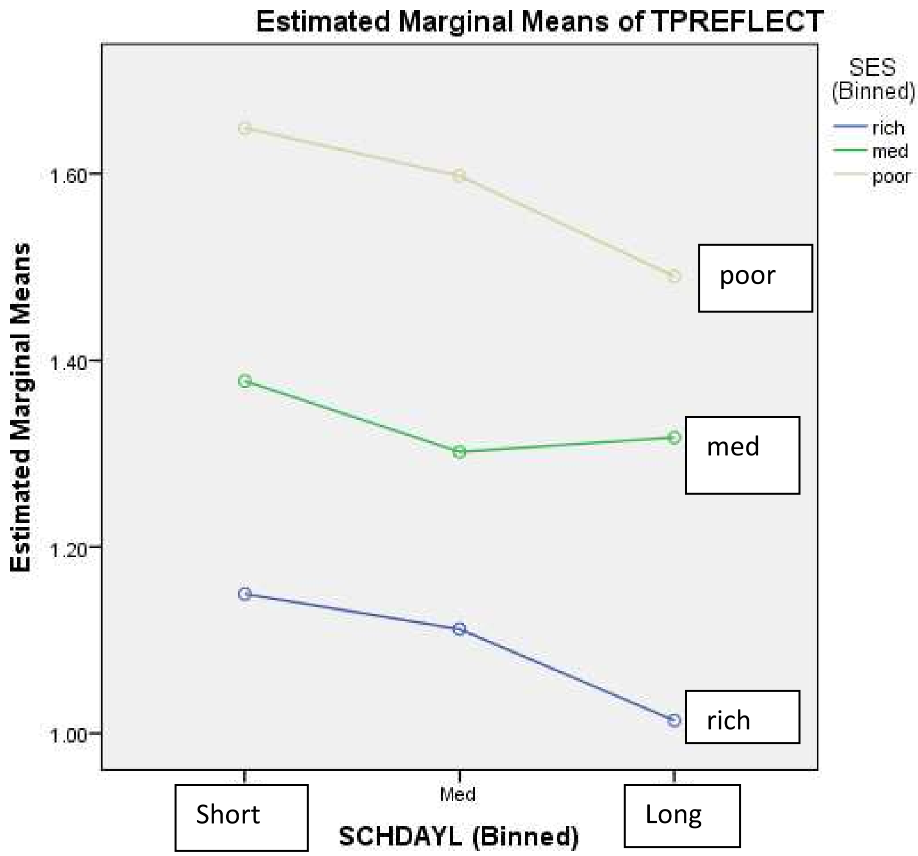


Figure 5. MA HSPA Scores Estimated Marginal Means with Transformed Variable (TPReflect)

An additional factorial ANCOVA was run using the same SES and SCHDAYL bins as before but with the addition of G11attend as a covariate. G11attend was selected as the covariate since this variable had the next highest significance after SES and SCHDAYL in the final hierarchical regression model. By controlling for G11attend, any differences between the binned groups, SES and SCHDAYL, found in the factorial ANOVA are more truly due to one of these two variables rather than an outside variable such as student attendance.

The results of this second factorial ANOVA were illuminated in Table 30. Similar to the first factorial ANOVA, there were significant differences between the SES groups $F(2, 316) = 72.6$, $p = .001 < .05$ and between the SCHDAYL bin $F(2, 316) = 5.35$, $p = .005$, which is $< .05$. In addition, there still was no interaction between the SES and SCHDAYL groups on the dependent variable $F(4, 316) = 1.28$, $p = 1.279 > .05$.

Table 30

MA Tests of Between-Subjects Effects with Transformed Dependent Variable (TPReflect) and Binned Factors and Covariate G11attend

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	17.141[a]	9	1.905	48.658	.000
Intercept	6.131	1	6.131	156.642	.000
G11attend	3.038	1	3.038	77.616	.000
schoolbin	.419	2	.209	5.350	.005
sesbin	5.680	2	2.840	72.553	.000
schoolbin * sesbin	.200	4	.050	1.276	.279
Error	12.369	316	.039		
Total	610.329	326			
Corrected Total	29.509	325			

a. R Squared = .581 (Adjusted R Squared = .569)

Analogous to what was executed in the first factorial ANOVA (See Figure 6), the chart below illustrates the plots of the estimated marginal means of the dependent variable, TPReflect, for the SCHDAYL groups and shown separately by SES bin while controlling for student attendance. The shape and position of line segments on this chart were almost identical to those presented on the first factorial ANOVA. Therefore, even when controlling for differences in student attendance rates between school categories the poor schools performed significantly lower than the median schools and the median schools performed significantly worse than the wealthier schools on the HSPA MA. Moreover, for both the poor and the rich schools, HSPA MA passing percentages improved when the school day length went from short to median length as well as when it went from median to long length. On the other hand, the line shown on the graph for the median SES schools was somewhat flatter than the corresponding line shown on the previous graph when there was no covariate. In summary, when median SES schools were controlled for by differences in student attendance rates, the length of the school day had little impact on the HSPA MA passing rates.

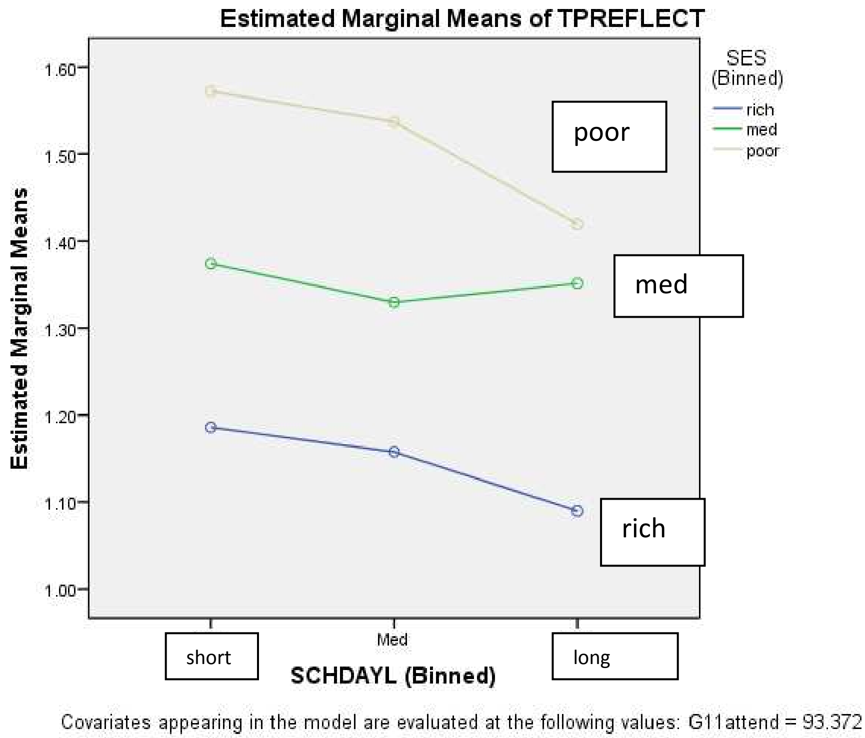


Figure 6. MA Estimated Marginal Means with Transformed Variable (TPReflect) with Binned SCHDAYL and SES

Univariate Analysis Non-Transformed Dependent Variable MA

A factorial ANCOVA was employed using the same SES and SCHDAYL binned groups along with G11attend as a covariate. However, in this factorial ANCOVA (See Table 31), the original dependent variable (TP+AP) was used rather than the transformed dependent variable (TPReflect). The descriptive statistics shows the mean HSPA MA passing percentage as well as the standard deviation of the passing percentages for each combination of SCHDAYL bin and

SES bin. Note that the descriptive table shows actual data with no adjustments for the G11attend covariate. An examination of this table shows that for both the rich and median SES schools, lengthening the school day from a short day to a median day as well as from a median day to a long day has little if any impact on HSPA MA passing rates. For the poor schools going from a short day to a median school day has little impact on the HSPA MA passing percentage, but going from a median school day length to a longer day increases the HSPA MA passing percentage by about five points.

Table 31

MA Descriptive Statistics Unstransformed Dependent Variable

Dependent Variable: TP+AP

SCHDAYL (Binned)	SES (Binned)	Mean	Std. Deviation	N
Short	rich	84.200	14.7786	28
	med	75.873	9.8221	44
	poor	53.881	16.1218	43
	Total	69.677	18.5635	115
Med	rich	86.947	5.7807	45
	med	79.277	8.6802	39
	poor	55.329	22.7492	28
	Total	76.371	18.0257	112
Long	rich	89.981	3.8974	36
	med	79.092	7.5966	26
	poor	60.273	22.0502	37
	Total	76.018	19.1435	99
Total	rich	87.243	8.8360	109
	med	77.859	8.9988	109
	poor	56.446	20.1055	108
	Total	73.903	18.7654	326

The tests of between-subjects table, Table 32 (from a third factorial ANOVA), presented a significant difference in the dependent variable (TP+AP) for the three SES groups $F(2, 316) = 75.24$, $p = .001 < .05$. Nevertheless, no significant differences between the three SCHDAYL groups $F(2, 316) = 1.74$, $p = .177 > .05$ was represented. Parallel to reported previously on the transformed scores, the untransformed scores revealed no significant interaction between the SES groups and SCHDAYL groups $F(4,316) = .94$, $p = .441 > .05$.

Table 32

MA Tests of Between-Subjects Effects Untransformed Dependent Variable (TP+AP)

Dependent Variable: TP+AP

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	75844.509[a]	9	8427.168	68.988	.000	.663
Intercept	10247.822	1	10247.822	83.893	.000	.210
G11attend	20145.620	1	20145.620	164.920	.000	.343
schoolbin	425.267	2	212.633	1.741	.177	.011
sesbin	18380.394	2	9190.197	75.235	.000	.323
schoolbin * sesbin	458.989	4	114.747	.939	.441	.012
Error	38600.519	316	122.154			
Total	1894932.510	326				
Corrected Total	114445.028	325				

a. R Squared = .663 (Adjusted R Squared = .653)

The estimated marginal means exposed each SCHDAYL/SES bin combination mean passing percentage, after controlling for differences in student attendance rates among the schools included in the study (See Table 33). Even when controlling for differences in student attendance rates, the length of the school day had little influence on HSPA MA passing percentages for the both rich schools and median SES schools. Relatedly, for the poor schools, lengthening the school day from a short to a median length had virtually no impact on HSPA MA passing rates. Interestingly, increasing the school day from a median length to a long length day resulted in a rise of about 6 percentage points in the passing rate on HSPA MA for poor schools.

Table 33

MA SCHDAYL and SES (Binned) Untransformed Dependent Variable (TP+AP)

Dependent Variable: TP+AP

SCHDAYL (Binned)	SES (Binned)	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
Short	rich	81.243[a]	2.101	77.109	85.378
	med	76.178[a]	1.666	72.900	79.457
	poor	60.130[a]	1.754	56.678	63.581
Med	rich	83.218[a]	1.673	79.927	86.510
	med	77.019[a]	1.778	73.520	80.518
	poor	60.271[a]	2.124	56.093	64.450
Long	rich	83.805[a]	1.904	80.060	87.551
	med	76.318[a]	2.178	72.032	80.603
	poor	66.017[a]	1.871	62.335	69.699

a. Covariates appearing in the model are evaluated at the following values: G11attend = 93.372.

Figure 7 displayed the plots of the estimated marginal means of the dependent variable, TP+AP, for the SCHDAYL shown separately by SES bin. The marginal means were adjusted to control for differences in student attendance rates between schools. The line segments for the poor, median, and rich schools were separate and distinct, which clearly confirmed that there were significant differences in HSPA MA performance between these three types of schools. Since we used the actual dependent variable, TP+AP, the order of the line segments show that the poor schools performed significantly lower than the median schools and the median schools performed significantly lower than the rich schools on the HSPA MA. Looking at the rich schools, there was a slight improvement in the HSPA MA passing percentage as the school day was lengthened from a short to a median day and from a median to long school day. For the median SES schools, there was little to no change in the passing percentage from short to median school day length; however, the passing percentage decreased slightly when the school day was lengthened from a median to a long day. Last, for the poor schools going from a short to a median school day had almost no effect on the HSPA MA passing percentage. Increasing the school day from a median to a long day for the SES poor schools did increase the passing percentage by about 6 points.

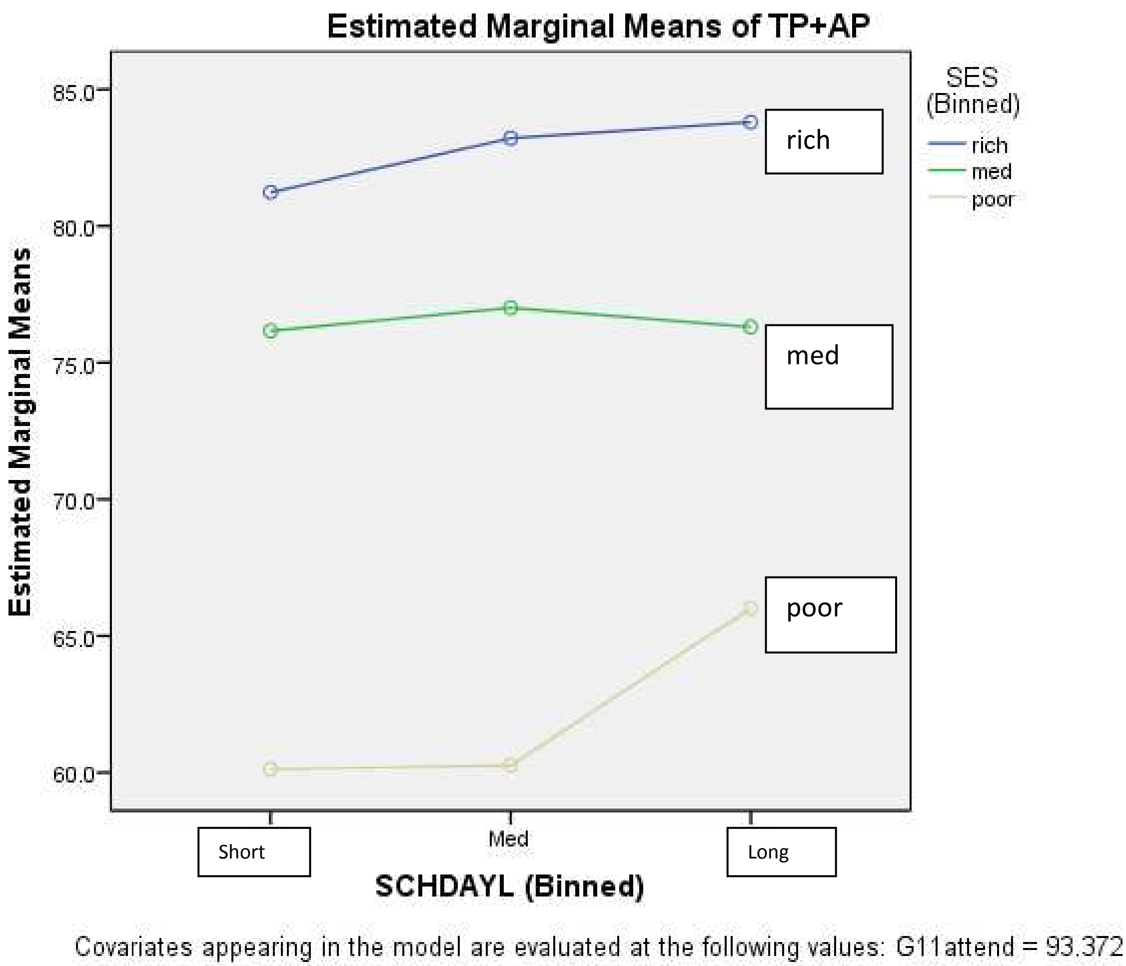


Figure 7. MA Estimated Marginal Means Untransformed Dependent Variable (TP+AP)

HSPA Language Arts (LA) Scores

Test of Normality Dependent Variable LA

Tests for normality on the population distribution were conducted on the dependent variable (TP+AP) by using the Explore command in SPSS. As a first step, a histogram of the

LA scores (TP+AP) for the sample of 326 schools was constructed. The results of the histogram revealed an asymmetrical distribution with a significant negative left skew (See Figure 8). "If a distribution has values of skew or kurtosis above or below 0, then this indicates a deviation from normal" (Field, 2013, p. 21). However, Field (2013) disclosed that "from the central limit theorem, in large samples (n > 30), the sample distribution tends to be normal, regardless of the shape of the data in the sample" (p. 871). Additionally, Field (2013) contends that the following:

(a) the assumption of normality tends to get translated as 'your data need to be normally distributed,' even though that's not really what it means"

(b) although it is often the shape of the sample distribution that matters, researchers tend to look at the scores on the outcome variable (or residuals) when assessing normality (p. 169)

Furthermore, "the central limit theorem means that there are a variety of situations in which we can assume normality regardless of the shape of our sample data" (Lumley, Diehr, Emerson & Chen, 2002, as cited by Field, 2013, p. 170).

Nevertheless, "histograms and descriptive statistics are a good way of getting an instant picture of the distribution of your data" (Field, 2009, p. 4).

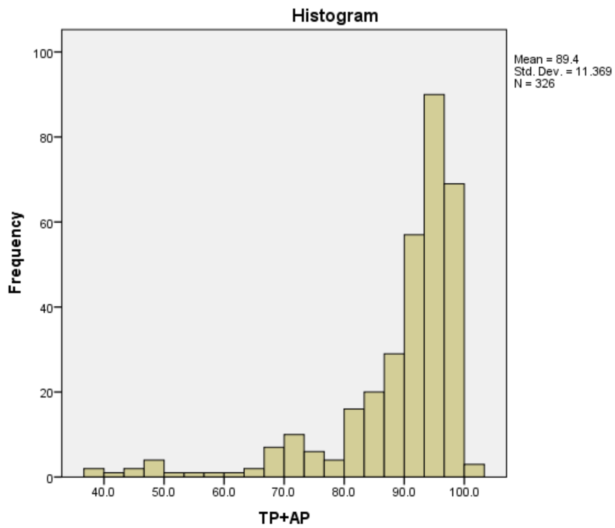


Figure 8. LA Normality Test Distribution Histogram Untransformed Dependent Variable (TP+AP)

To further explore the degree of negative skewness of the LA dependent variable (TP+AP), the normality of the data was assessed by calculating skewness and kurtosis statistics.

For the HSPA LA scores in Table 34, the z-score of skewness is z = -2.344/.135 = -17.36; the z-scores are significant at α = .05 because they lie outside the -1.96 to 1.96 range (Field, 2013, p. 179). The interpretation of the skewness based on the z-score was that the distribution of the LA passing percentages (TP+AP) was significantly negatively skewed. The kurtosis z-score was 6.016/.269 = 22.36.   Because the z-score was greater than 1.96, this denoted that the distribution of the LA scores had a significant positive kurtosis. Both the significant skewness and kurtosis suggested a non-normal distribution.   All data were re-verified to assure that all numbers were entered correctly into the data set from the NJDOE site.

Table 34

LA Descriptives Untransformed Dependent Variable (TP+AP)

			Statistic	Std. Error
TP+AP	Mean		89.396	.6297
	95% Confidence Interval for Mean	Lower Bound	88.157	
		Upper Bound	90.635	
	5% Trimmed Mean		90.951	
	Median		93.300	
	Variance		129.248	
	Std. Deviation		11.3687	
	Minimum		37.9	
	Maximum		100.0	
	Range		62.1	
	Interquartile Range		9.0	
	Skewness		-2.344	.135
	Kurtosis		6.016	.269

The test of normality of the distribution was further supported by the Kolmogorov-Smirnov (K-S) and Shapiro-Wilk (S-W) tests. Both tests reveal statistically significant results: for K-S, D(326) =.20, p = .001 <.05 and S-W, W(326) = .73, p = .0001 <.05.

Table 35

LA Tests of Normality Untransformed Dependent Variable

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
TP+AP	.203	326	.000	.725	326	.000

a. Lilliefors Significance Correction

To correct negatively skewed data, Field (2009, p. 155) advised that you first reverse the scores (subtracting each score from the highest score in the data set +1); in this data set each HSPA LA passing percentage (TP+AP) was subtracted from the number 101. Reversing the scores turns a negatively skewed distribution into a positively skewed one. Subsequently, to correct the positive skew of this reversed distribution, Field (2009, p. 155) recommends running a transformation in SPSS as a second step. In this analysis, the researcher applied a logarithm transformation (log10) in SPSS and converted the dependent variable into a more symmetrical distribution; the final transformed distribution of passing scores was labeled TPLA_Reflext. The TPLA_Reflext histogram (See Figure 9) became much less skewed than the original TP+AP distribution but the distribution of transformed scores still had a slight left negative skew.

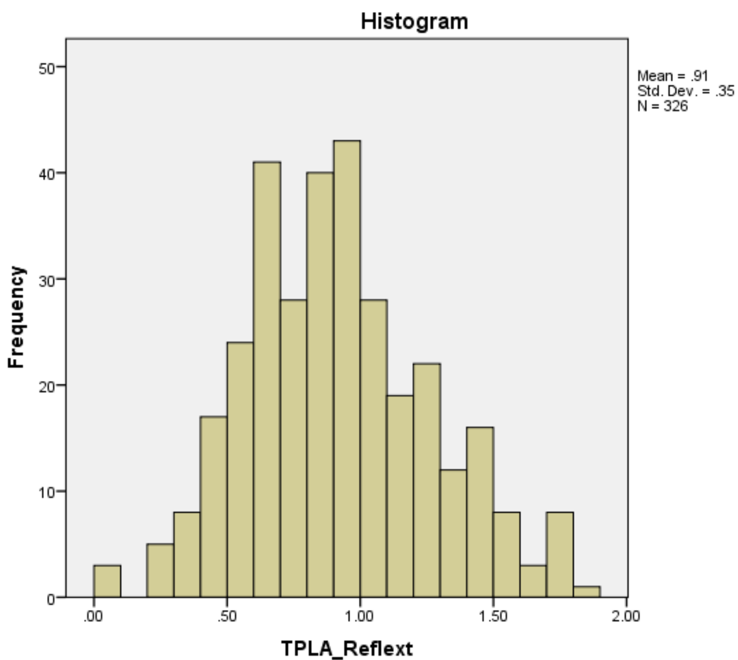


Figure 9. LA Distribution Histogram Transformed Dependent Variable TPLA_Reflext

The descriptive statistics for TPLA_Reflext (See Table 36) exposed the improved skewness statistic; skewness z-score =.309 / 1.35 = 2.29 and kurtosis z-score = -.105 / .269 = -0.39. While the skewness z-score was statistically significant (since they fall outside of the -1.96 to 1.96 range), it was far less extreme than the non-transformed data. However, Field (2008) states the following:

> An absolute value greater than 1.96 is significant at p <.05, above 2.58 is significant at p < .01, and absolute values above about 3.29 are significant at p < .001. Large samples will give rise to small standard errors and so when sample sizes are big, significant values

arise from even small deviations from normality. In most samples it's OK to look for values above 1.96; however, in large samples this criterion should be increased to 2.58 or 3.29 and in very large samples, because of the problem of small standard errors that I've described, no criterion should be applied to all! (p. 7).

The important value of a z is 1.96 because this cuts off the top 2.5% of the distribution, and its counterpart at the opposite end (-1.96) cuts off the bottom 2.5% of the distribution. As such, taken together, this value cuts off 5% of scores, or put another way, 95% of z-scores lie between -1.96 and 1.96. The two important benchmarks are +2.58 and +3.29, which cut off 1% of scores respectively. Put another way, 99% of z-scores lie between -2.58 and 2.58, and 99.9% of them lie between -3.29 and 3.29 (Field, 2013, p. 180).

Table 36

LA Descriptives Transformed Dependent Variable (TPLA_Reflext)

			Statistic	Std. Error
TPLA_Reflext	Mean		.9149	.01940
	95% Confidence Interval for Mean	Lower Bound	.8768	
		Upper Bound	.9531	
	5% Trimmed Mean		.9085	
	Median		.8865	
	Variance		.123	
	Std. Deviation		.35032	
	Minimum		.00	
	Maximum		1.80	
	Range		1.80	
	Interquartile Range		.47	
	Skewness		.309	.135
	Kurtosis		-.105	.269

The tests of normality on the transformed data (TPLA_Reflext) were both significant (See Table 37): for K-S, D(326) = .06, $p = .006 < .05$ and for S-W, W(326) = .99, $p = .003 < .05$. Since the transformed dependent variable (TPLA_Reflext) represented a much closer to normal distribution than the untransformed dependent variable (TP+AP) and the fact that the sample size of 326 schools was relatively large, the transformed variable (TPLA_Reflext) was chosen and used in subsequent regression analyses.

Table 37

LA Tests of Normality Transformed Dependent Variable (TPLA_Reflext)

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.
TPLA_Reflext	.060	326	.006	.986	326	.003

a. Lilliefors Significance Correction

Simultaneous Regression LA

The first analysis run in SPSS for HSPA LA was a regression using the enter method that included all the selected independent variables obtained from 2011 NJ School Report Card data. The purpose of this regression was to determine and show which variables had a significant influence on the HSPA passing percentages as well as to identify potential mulitcollinearity issues between predictor variables. Predictor variables found to be strongly related (those with a Pearson Linear Correlation Coefficient (r) of $r > .60$ or $r < -.60$) informed the researcher of potential multicollinearity issues within the regression model. Table 38 captured the means and standard deviations of the dependent (TPLA_Reflext) and the independent variables.

Table 38

LA Descriptive Statistics Transformed Dependent Variable (TPLA_Reflext)

	Mean	Std. Deviation	N
TPLA_Reflext	.9149	.35032	326
G11attend	93.372	3.2624	326
SCHDAYL	410.74	27.435	326
STMOB	9.579	11.2019	326
SES	27.137	27.2654	326
LEP	1.142	3.6874	326
DIS	1.765	4.6911	326
FATTEND	95.633	7.7370	326
FMOBILITY	4.313	5.4614	326
MA+	51.830	14.0925	326
enrG9to12	1095.531	599.7438	326

The correlation matrix (See Table 39) presented the Pearson correlation coefficient r between each pair of variables, including the independent variable; also depicted was the statistical significance (*p*-value) of each correlation coefficient. Among the possible pairs of independent variables, the strongest, statistically significant correlations were between G11attend and STMOB (r = -.67, p =.0001 <.05) and between LEP and DIS (r = .76, p =.0001 <.05).

Table 39

LA Correlations Transformed Dependent Variable (TPLA_Reflext)

		TPLA_Reflext	G11attend	SCHDAYL	STMOB	SES	LEP	DIS	FATTEND	FMOBILITY	MA+	enrG9to12
Pearson Correlation	TPLA_Reflext	1.000	-.657	-.106	.652	.694	.348	.294	-.206	.135	-.366	-.151
	G11attend	-.657	1.000	.054	-.670	-.546	-.216	-.189	.367	-.296	.261	.143
	SCHDAYL	-.106	.054	1.000	-.044	.191	.114	.040	.121	.095	.078	-.070
	STMOB	.652	-.670	-.044	1.000	.552	.166	.100	-.023	.228	-.313	-.219
	SES	.694	-.546	.191	.552	1.000	.348	.261	-.148	.193	-.361	-.182
	LEP	.348	-.216	.114	.166	.348	1.000	.760	-.009	.034	-.016	.261
	DIS	.294	-.189	.040	.100	.261	.760	1.000	-.001	.044	.021	.369
	FATTEND	-.206	.367	.121	-.023	-.148	-.009	-.001	1.000	.016	.022	.050
	FMOBILITY	.135	-.296	.095	.228	.193	.034	.044	.016	1.000	-.081	-.121
	MA+	-.366	.261	.078	-.313	-.361	-.016	.021	.022	-.081	1.000	.098
	enrG9to12	-.151	.143	-.070	-.219	-.182	.261	.369	.050	-.121	.098	1.000
Sig. (1-tailed)	TPLA_Reflext	.	.000	.027	.000	.000	.000	.000	.000	.007	.000	.003
	G11attend	.000	.	.167	.000	.000	.000	.000	.000	.000	.000	.005
	SCHDAYL	.027	.167	.	.214	.000	.020	.238	.014	.044	.079	.104
	STMOB	.000	.000	.214	.	.000	.001	.035	.342	.000	.000	.000
	SES	.000	.000	.000	.000	.	.000	.000	.004	.000	.000	.000
	LEP	.000	.000	.020	.001	.000	.	.000	.437	.271	.384	.000
	DIS	.000	.000	.238	.035	.000	.000	.	.495	.213	.355	.000
	FATTEND	.000	.000	.014	.342	.004	.437	.495	.	.383	.348	.185
	FMOBILITY	.007	.000	.044	.000	.000	.271	.213	.383	.	.072	.015
	MA+	.000	.000	.079	.000	.000	.384	.355	.348	.072	.	.039
	enrG9to12	.003	.005	.104	.000	.000	.000	.000	.185	.015	.039	.
N	TPLA_Reflext	326	326	326	326	326	326	326	326	326	326	326
	G11attend	326	326	326	326	326	326	326	326	326	326	326
	SCHDAYL	326	326	326	326	326	326	326	326	326	326	326
	STMOB	326	326	326	326	326	326	326	326	326	326	326
	SES	326	326	326	326	326	326	326	326	326	326	326
	LEP	326	326	326	326	326	326	326	326	326	326	326
	DIS	326	326	326	326	326	326	326	326	326	326	326
	FATTEND	326	326	326	326	326	326	326	326	326	326	326
	FMOBILITY	326	326	326	326	326	326	326	326	326	326	326
	MA+	326	326	326	326	326	326	326	326	326	326	326
	enrG9to12	326	326	326	326	326	326	326	326	326	326	326

The ANOVA reported in Table 40 confirmed that the overall model's regression was significant F (10,315) = 66.64, $p < .0001$.

Table 40

LA ANOVA[a] Transformed Dependent Variable (TPLA_Reflext)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	27.083	10	2.708	66.640	.000[b]
	Residual	12.802	315	.041		
	Total	39.885	325			

a. Dependent Variable: TPLA_Reflext
b. Predictors: (Constant), enrG9to12, FATTEND, MA+, FMOBILITY, SCHDAYL, LEP, STMOB, SES, DIS, G11attend

The model summary in Table 41 illustrated an adjusted R^2 of 67%, which indicated that 67% of the variance in the dependent variable is explained by the model (i.e., by the variations in the predictor variables). The Durbin-Watson statistic of 1.939 showed no significant auto correlation in the corresponding residuals.

Table 41

LA Model Summary[b] Transformed Dependent Variable (TPLA_Reflext)

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.824[a]	.679	.669	.20160	.679	66.640	10	315	.000	1.939

a. Predictors: (Constant), enrG9to12, FATTEND, MA+, FMOBILITY, SCHDAYL, LEP, STMOB, SES, DIS, G11attend
b. Dependent Variable: TPLA_Reflext

The independent variables shown (in the Coefficients Table 42) G11attend, SCHDAYL, STMOB, SES, and MA+ all had a significant influence on the dependent variable (TPLA_Reflext); the *p*-values associated with these variables were less than .05. The standardized Beta (β) showed the strength and direction of the relationship between the given independent variable and dependent variable. Because TPLA_Reflext was a transformed dependent variable (it involved a reversal of the original dependent variable scores), independent variables with positive β's actually had a negative influence on the original TP+AP dependent variable (HSPA passing percentages). Similarly, independent variables with negative β's had a positive influence on the dependent variable.

The variables with the greatest to least significance with positive influence were G11attend, SCHDAYL, MA+, enrG9to12, FMOBILTY, and FATTEND; alternatively, the negative influencers in the order of most to least significance were SES, STMOB, DIS, and LEP. Caution should be exercised when interpreting the β values associated with independent variables that are highly correlated with other independent variables in the model, including STMOB, G11attend, LEP and DIS.

The Tolerance and VIF collinearity statistics in the model provided further substantiation of predictor variables that were highly correlated with other independent variables. A VIF statistic greater than 2 indicated a high correlation for G11attend (2.673), DIS (2.625), LEP (2.547), STMOB (2.341), and SES (2.057).

Table 42

LA Coefficients[a] Transformed Dependent Variable (TPLA_Reflext)

Model		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	4.042	.499		8.097	.000					
	G11attend	-.023	.006	-.218	-4.178	.000	-.657	-.229	-.133	.374	2.673
	SCHDAYL	-.002	.000	-.160	-4.647	.000	-.106	-.253	-.148	.865	1.157
	STMOB	.007	.002	.235	4.817	.000	.652	.262	.154	.427	2.341
	SES	.005	.001	.383	8.356	.000	.694	.426	.267	.486	2.057
	LEP	.009	.005	.093	1.830	.068	.348	.103	.058	.393	2.547
	DIS	.007	.004	.095	1.832	.068	.294	.103	.058	.381	2.625
	FATTEND	-.002	.002	-.037	-1.008	.314	-.206	-.057	-.032	.737	1.356
	FMOBILITY	-.004	.002	-.064	-1.875	.062	.135	-.105	-.060	.877	1.140
	MA+	-.002	.001	-.083	-2.359	.019	-.366	-.132	-.075	.817	1.224
	enrG9to12	-3.933E-5	.000	-.067	-1.834	.068	-.151	-.103	-.059	.756	1.322

a. Dependent Variable: TPLA_Reflect

Using the backward method, a second multiple regression analysis was run in SPSS, (See Table 43). Before actually running this model, two of the independent variables (STMOB and LEP) were removed (as previously explained) to eliminate any multicollinearity issues. Except for STMOB and LEP, all the independent significant variables were entered. The significance of each independent variable was verified, and the variable with the least significance (with the highest *p*-value) was noted.

Table 43

LA Descriptive Statistics Transformed Dependent Variable (TPLA_Reflext)

	Mean	Std. Deviation	N
TPLA_Reflext	.9149	.35032	326
G11attend	93.372	3.2624	326
SCHDAYL	410.74	27.435	326
SES	27.137	27.2654	326
DIS	1.765	4.6911	326
FATTEND	95.633	7.7370	326
FMOBILITY	4.313	5.4614	326
MA+	51.830	14.0925	326
enrG9to12	1095.531	599.7438	326

The results from the ANOVA (See Table 44) suggested that although all the regression models were significant, Model 2 contained the following independent variables: enrG9to12, MA+, FMOBILITY, SCHDAYL, DIS, G11attend, and SES. The regression statistics for Model 2 were $F(7, 318) = 84.69$, $p = .0001 < .05$.

Table 44

LA ANOVA[a] Selected Variables Transformed Dependent Variable (TPLA_Reflext)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25.978	8	3.247	74.020	.000[b]
	Residual	13.907	317	.044		
	Total	39.885	325			
2	Regression	25.960	7	3.709	84.690	.000[c]
	Residual	13.925	318	.044		
	Total	39.885	325			

a. Dependent Variable: TPLA_Reflext
b. Predictors: (Constant), enrG9to12, FATTEND, MA+, FMOBILITY, SCHDAYL, DIS, G11attend, SES
c. Predictors: (Constant), enrG9to12, MA+, FMOBILITY, SCHDAYL, DIS, G11attend, SES

The results from the model summary (See Table 45) highlighted that Model 2's adjusted R^2 was 64.3 %, meaning that 64.3% of the variation in the dependent variable (TPLA_Reflext) can be explained by this model. An examination of the model further showed that the elimination of the non-significant variable (FATTEND) had little effect on the predictive power of the model (the adjusted R^2 remained at 64.3%). The fact that the Durbin Watson statistic of 1.986 was close to 2 indicated that no significant auto correlations in the residuals produced by this model exist.

Table 45

LA Model Summary[c] Selected Variables Transformed Dependent Variable (TPLA_Reflext)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.807[a]	.651	.643	.20945	.651	74.020	8	317	.000	
2	.807[b]	.651	.643	.20926	.000	.417	1	317	.519	1.986

a. Predictors: (Constant), enrG9to12, FATTEND, MA+, FMOBILITY, SCHDAYL, DIS, G11attend, SES
b. Predictors: (Constant), enrG9to12, MA+, FMOBILITY, SCHDAYL, DIS, G11attend, SES
c. Dependent Variable: TPLA_Reflext

As shown in the Coefficients Table 46, except for FMOBILITY, all the independent variables in Model 2 were significant and had *p*-values of less than .05. In addition, G11attend, SCHDAYL, MA+, enrG9to12, and FMOBILITY had negative standardized beta values indicating that these variables had a positive relationship with the original dependent variable (TP+AP). In contrast, both SES and DIS had positive standardized beta values indicating that the variables had a negative influence on the LA passing percentage (TP+AP). In summary, the independent variables in order of influence on the dependent variable (based on their beta) were SES (.458), G11attend (-.352), SCHDAYL (-.173), DIS (.151), MA+ (-.096), engG9to12 (-.084), and FMOBILTY (-.066).

The fact that the VIF (variance inflation factor) figures for each of the independent variables were less than 2 confirmed that this final model had no multicollinearity issues.

Table 46

LA Coefficients[a] Transformed Dependent Variable TPLA_Reflext

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardizd Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	5.378	.428		12.564	.000					
	G11attend	-.039	.005	-.362	-8.083	.000	-.657	-.413	-.268	.548	1.825
	SCHDAYL	-.002	.000	-.175	-4.983	.000	-.106	-.270	-.165	.887	1.128
	SES	.006	.001	.458	10.188	.000	.694	.497	.338	.543	1.840
	DIS	.011	.003	.150	3.848	.000	.294	.211	.128	.728	1.373
	FATTEND	.001	.002	.024	.645	.519	-.206	.036	.021	.829	1.207
	FMOBILITY	-.004	.002	-.069	-1.959	.051	.135	-.109	-.065	.880	1.137
	MA+	-.002	.001	-.093	-2.552	.011	-.366	-.142	-.085	.822	1.216
	enrG9to12	-4.916E-5	.000	-.084	-2.224	.027	-.151	-.124	-.074	.768	1.302
2	(Constant)	5.368	.427		12.560	.000					
	G11attend	-.038	.004	-.352	-8.406	.000	-.657	-.426	-.279	.627	1.596
	SCHDAYL	-.002	.000	-.173	-4.949	.000	-.106	-.267	-.164	.895	1.118
	SES	.006	.001	.458	10.193	.000	.694	.496	.338	.544	1.840
	DIS	.011	.003	.151	3.913	.000	.294	.214	.130	.733	1.365
	FMOBILITY	-.004	.002	-.066	-1.893	.059	.135	-.106	-.063	.895	1.118
	MA+	-.002	.001	-.096	-2.625	.009	-.366	-.146	-.087	.829	1.206
	enrG9to12	-4.935E-5	.000	-.084	-2.235	.026	-.151	-.124	-.074	.768	1.302

a. Dependent Variable: TPLA_Reflext

Hierarchical Regression LA

A hierarchical regression (See Table 47) was run using the six significant variables (i.e., those with a *p*-value of less than .05) obtained in the final model of the backwards regression. Each variable was entered one by one based on the magnitudes of their betas with the largest beta entered first.

Table 47

LA Descriptive Statistics Transformed Dependent Variable (TPLA_Reflect)

	Mean	Std. Deviation	N
TPLA_Reflext	.9149	.35032	326
SES	27.137	27.2654	326
G11attend	93.372	3.2624	326
SCHDAYL	410.74	27.435	326
DIS	1.765	4.6911	326
MA+	51.830	14.0925	326
enrG9to12	1095.531	599.7438	326

The results from the ANOVA Table 48 revealed that each of the six iterations of the hierarchical model were statistically significant, with the final model having the following statistics $F(6, 319) = 97.42$, $p = .0001 < .05$.

Table 48

LA ANOVA[a] Transformed Dependent Variable (TPLA_Reflext)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	19.184	1	19.184	300.266	.000[b]
	Residual	20.701	324	.064		
	Total	39.885	325			
2	Regression	23.596	2	11.798	233.960	.000[c]
	Residual	16.288	323	.050		
	Total	39.885	325			
3	Regression	24.934	3	8.311	179.006	.000[d]
	Residual	14.951	322	.046		
	Total	39.885	325			
4	Regression	25.322	4	6.331	139.545	.000[e]
	Residual	14.563	321	.045		
	Total	39.885	325			
5	Regression	25.609	5	5.122	114.811	.000[f]
	Residual	14.276	320	.045		
	Total	39.885	325			
6	Regression	25.803	6	4.300	97.419	.000[g]
	Residual	14.082	319	.044		
	Total	39.885	325			

a. Dependent Variable: TPLA_Reflext
b. Predictors: (Constant), SES
c. Predictors: (Constant), SES, G11attend
d. Predictors: (Constant), SES, G11attend, SCHDAYL
e. Predictors: (Constant), SES, G11attend, SCHDAYL, DIS
f. Predictors: (Constant), SES, G11attend, SCHDAYL, DIS, MA+
g. Predictors: (Constant), SES, G11attend, SCHDAYL, DIS, MA+, enrG9to12

The model summary (See Table 49) results demonstrated that Model 6's adjusted R^2 was 64%; therefore, 64% of the variation in the dependent variable (TPLA_Reflext, HSPA LA passing percentages) can be explained by this model. The R^2 change column showed the contributions of each independent variable on the predictive capability of the model. SES contributed 48.1% to the predictive power of the model, while G11attend contributed 11.1%, SCHDAYL contributed 3.4%, DIS contributed 1.0%, MA+ contributed .7%, and enrG9to12 contributed .5%.

The fact that the Durbin Watson statistic of 1.986 was close to 2 indicated that no significant auto correlations in the residuals were produced by the model. “As a very conservative rule of thumb, values less 1 or greater than 3 are definitely cause for concern” (Field, 2013, p. 311).

Table 49

LA Model Summary [g] Transformed Dependent Variable (TPLA_Reflext)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.694[a]	.481	.479	.25277	.481	300.266	1	324	.000	
2	.769[b]	.592	.589	.22456	.111	87.495	1	323	.000	
3	.791[c]	.625	.622	.21548	.034	28.811	1	322	.000	
4	.797[d]	.635	.630	.21299	.010	8.557	1	321	.004	
5	.801[e]	.642	.636	.21121	.007	6.431	1	320	.012	
6	.804[f]	.647	.640	.21011	.005	4.385	1	319	.037	1.986

a. Predictors: (Constant), SES
b. Predictors: (Constant), SES, G11attend
c. Predictors: (Constant), SES, G11attend, SCHDAYL
d. Predictors: (Constant), SES, G11attend, SCHDAYL, DIS
e. Predictors: (Constant), SES, G11attend, SCHDAYL, DIS, MA+
f. Predictors: (Constant), SES, G11attend, SCHDAYL, DIS, MA+, enrG9to12
g. Dependent Variable: TPLA_Reflext

The coefficients (See Table 50) results illustrated that in the sixth hierarchical model, G11attend, SCHDAYL, MA+, and enrG9to12 had positive influences on the original dependent variable as evidenced by their negative betas, while SES and DIS had a negative impact on the HSPA LA passing percentages because these variables had positive betas. The fact that the

VIF's for all six independent variables were less than 2 signified that no multicollinearity issues existed in the model.

Table 50

LA Coefficients[a] Transformed Dependent Variable (TPLA_Reflext)

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	.673	.020		34.054	.000					
	SES	.009	.001	.694	17.328	.000	.694	.694	.694	1.000	1.000
2	(Constant)	4.728	.434		10.898	.000					
	SES	.006	.001	.477	11.239	.000	.694	.530	.400	.702	1.424
	G11attend	-.043	.005	-.397	-9.354	.000	-.657	-.462	-.333	.702	1.424
3	(Constant)	5.276	.429		12.308	.000					
	SES	.007	.001	.537	12.714	.000	.694	.578	.434	.653	1.531
	G11attend	-.038	.004	-.354	-8.535	.000	-.657	-.430	-.291	.676	1.479
	SCHDAYL	-.002	.000	-.190	-5.368	.000	-.106	-.287	-.183	.928	1.078
4	(Constant)	5.203	.424		12.259	.000					
	SES	.007	.001	.514	12.095	.000	.694	.560	.408	.631	1.585
	G11attend	-.037	.004	-.347	-8.458	.000	-.657	-.427	-.285	.674	1.483
	SCHDAYL	-.002	.000	-.190	-5.430	.000	-.106	-.290	-.183	.928	1.078
	DIS	.008	.003	.102	2.925	.004	.294	.161	.099	.929	1.077
5	(Constant)	5.200	.421		12.356	.000					
	SES	.006	.001	.478	10.759	.000	.694	.515	.360	.567	1.763
	G11attend	-.037	.004	-.341	-8.358	.000	-.657	-.423	-.280	.672	1.489
	SCHDAYL	-.002	.000	-.177	-5.035	.000	-.106	-.271	-.168	.907	1.103
	DIS	.009	.003	.114	3.264	.001	.294	.179	.109	.912	1.097
	MA+	-.002	.001	-.093	-2.536	.012	-.366	-.140	-.085	.830	1.205
6	(Constant)	5.191	.419		12.398	.000					
	SES	.006	.001	.459	10.161	.000	.694	.494	.338	.544	1.840
	G11attend	-.036	.004	-.333	-8.159	.000	-.657	-.415	-.271	.665	1.503
	SCHDAYL	-.002	.000	-.180	-5.157	.000	-.106	-.277	-.172	.905	1.105
	DIS	.011	.003	.150	3.869	.000	.294	.212	.129	.733	1.364
	MA+	-.002	.001	-.095	-2.599	.010	-.366	-.144	-.086	.829	1.206
	enrG9to12	-4.631E-5	.000	-.079	-2.094	.037	-.151	-.116	-.070	.772	1.295

a. Dependent Variable: TPLA_Reflext

Univariate Analysis of Transformed Dependent Variable LA

A Univariate Analysis of Variance (See Table 51) was performed to secure a better understanding of the impact of the two most significant independent variables (SES and SCHDAYL) on the HSPA LA passing percentage. The dependent variable used in this ANOVA was the transformed dependent variable (TPLA_Reflext). Two sets of grouping variables were created. For SES, the schools were grouped into three approximately equal-sized bins and labeled rich, median, and poor based on the percentage of SES students. Similarly, for SCHDAYL the schools were grouped into three equal-sized bins (labeled short, median, and long) based on the length of school day reported by the NJDOE. The number of schools included in each grouping bin (SCHDAYL and SES) can be seen in Table 51 below.

Table 51

LA Between-Subjects Factors Transformed Dependent Variable (TPLA_Reflext)

		Value Label	N
SES (Binned)	1	Rich	109
	2	Med	109
	3	Poor	108
SCHDAYL (Binned)	1	Short	115
	2	Med	112
	3	Long	99

The results of the factorial ANOVA analysis performed on the binned data can be seen in the Tests of Between-Subjects Effects Table (See Table 52). There were significant differences in the dependent variable (TPLA_Reflext) between the SES bins $F(2, 317) = 156.42$, $p = .0001 < .05$ as well as between the SCHDAYL bins $F(2, 317) = 3.76$, $p = .024 < .05$. However, no significant interaction between the SES bins and the SCHDAYL bins on the dependent variable (TPLA_Reflext) were found; the interaction statistics were $F(4, 317) = 1.15$, $p = .332 < .05$.

Table 52

LA Univariate Analysis of Variance Tests of Between-Subjects Effects with Binned SES and SCHDAYL with Transformed Dependent Variable (TPLA_Reflext)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	20.506[a]	8	2.563	41.928	.000
Intercept	260.669	1	260.669	4263.955	.000
sesbinnedla	19.125	2	9.563	156.421	.000
sesbinnedla * schbinLA	.282	4	.070	1.153	.332
schbinLA	.460	2	.230	3.760	.024
Error	19.379	317	.061		
Total	312.787	326			
Corrected Total	39.885	325			

a. R Squared = .514 (Adjusted R Squared = .502)

Post Hoc Tests LA

A Tukey HSD post hoc test (multiple comparisons on SCHDAYL) was performed in order to determine the exact differences between the binned groups (See Table 53). For the SCHDAYL groups, significant differences in the transformed dependent variable (TPLA_Reflext) were found between the short and median bins and the short and long bins; however, no significant differences were found in the dependent variable between the median and high-binned schools. Because we used the transformed variable that involved a reversal, the fact that the differences in the dependent variable between the median and short bins was negative indicated that schools that had a median length day performed better than schools that had a shorter day. The mean difference between the long and short schools was negative and therefore the schools that had a longer school day performed better on the HSPA LA than the schools that had a shorter day.

Table 53

LA Multiple Comparisons Tukey HSD with Transformed Dependent Variable (TPLA_Reflext)

(I) SCHDAYL (Binned)	(J) SCHDAYL (Binned)	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
short	med	.1150*	.03282	.002	.0377	.1923
	long	.1323*	.03390	.000	.0525	.2121
med	short	-.1150*	.03282	.002	-.1923	-.0377
	long	.0173	.03411	.868	-.0630	.0976
long	short	-.1323*	.03390	.000	-.2121	-.0525
	med	-.0173	.03411	.868	-.0976	.0630

Based on observed means.
The error term is Mean Square(Error) = .061.
* The mean difference is significant at the .05 level.

A Tukey HSD post hoc test (multiple comparisons) was run on the SES binned groups and can be seen in Table 54. The post hoc showed that there were significant differences between (a) rich and median districts, (b) rich and poor districts, and (c) median and poor districts. Because the dependent variable (TPLA_Reflext) was a transformed variable which involved a reversal of scores, the fact that difference in the dependent variable between rich and median schools was negative indicated that rich schools performed better on the HSPA LA than median schools. Similarly, the fact that the difference between rich and poor schools was negative reflected that rich districts performed better on the HSPA LA than poor schools. Finally, the difference between median and poor schools was also negative, which meant that schools with median status performed better on the HSPA MA than schools with poorer students.

Table 54

*LA Tukey HSD Multiple Comparisons with Transformed Dependent Variable (*TPLA_Reflext)

(I) SES (Binned)	(J) SES (Binned)	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
rich	med	-.2548*	.03349	.000	-.3337	-.1759
	poor	-.5999*	.03357	.000	-.6790	-.5209
med	rich	.2548*	.03349	.000	.1759	.3337
	poor	-.3451*	.03357	.000	-.4242	-.2661
poor	rich	.5999*	.03357	.000	.5209	.6790
	med	.3451*	.03357	.000	.2661	.4242

Based on observed means.
The error term is Mean Square (Error) = .061.
* The mean difference is significant at the .05 level.

The following chart (See Figure 10) depicted the plots of the estimated marginal means for the transformed dependent variable, TPLA_Reflext, for the SCHDAYL and was shown separately by SES bin. The line segments for the poor, median, and rich schools were separate and distinct, which clearly illustrated significant differences in HSPA LA performance between the three types of schools (poor, median, rich). Because the transformation of the dependent variable, TPLA_Reflext, involved a reversal of the scores, the order in which the line segments appeared on the graph clearly depicted that the poor schools performed significantly lower than the median schools and that the median schools performed significantly worse than the wealthier schools on the HSPA LA. For the poor schools, the lines sloped downward. Because the dependent variable, TPLA_Reflext, involved a reversal of scores, this meant that HSPA LA test performance improved for poor schools as the school day grew longer (from a short to median length as well as when it increased from a median to long length). Nevertheless, although the schools in the median SES bin showed some improvement in LA test performance when the school day was increased from a short day to a median length school day, there was virtually no change in performance when the school day changed from a median length to a longer day.

For the wealthy SES binned schools HSPA LA test performance exhibited little change when going from a short day to a median day but improved slightly when going from a median to a longer day.

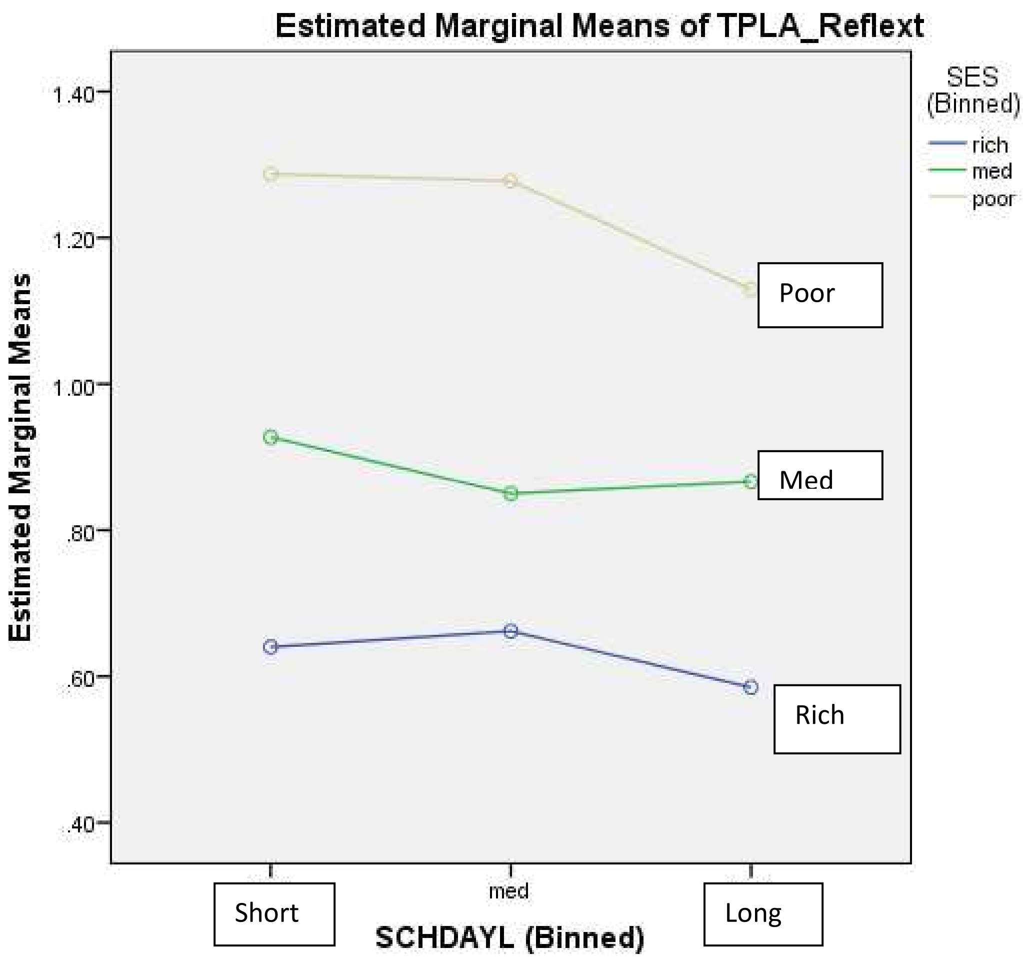


Figure 10. LA Estimated Marginal Means Transformed Dependent Variable (TPLA_Reflext) with Binned SCHDAYL and SES

A second factorial ANCOVA was run using the same SES and SCHDAYL bins as before but with the addition of G11attend as a covariate. G11attend was selected as the covariate because this variable also had significant influence on the dependent variable as measured by the magnitude of its standardized beta in the final hierarchical regression model. By controlling for G11attend, any differences between SES and SCHDAYL binned groups found in the factorial

ANCOVA are more truly due to one of these two variables rather than an outside variable such as student attendance.

The test of between-subject effects (See Table 55) illuminated the results of this second factorial ANOVA. Similar to the first factorial ANOVA, there were significant differences between the SES groups $F(2, 316) = 80.28$, $p = .0001 < .05$ but no significant differences between the SCHDAYL bins $F(2, 316) = 2.47$, $p = .086 > .05$. In addition, there still was no interaction between the SES and SCHDAYL groups on the dependent variable $F(4, 316) = 1.69$, $p = .152 > .05$.

Table 55

LA Tests of Between-Subject Effects (Second Factorial ANCOVA) with Transformed Dependent Variable (TPLA_Reflext) and Binned Factors with Covariate G11attend

	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	25.253[a]	9	2.806	60.596	.000	.633	545.363	1.000
Intercept	7.124	1	7.124	153.851	.000	.327	153.851	1.000
G11attend	4.747	1	4.747	102.518	.000	.245	102.518	1.000
sesbinnedla	7.435	2	3.717	80.280	.000	.337	160.560	1.000
schbinLA	.229	2	.114	2.472	.086	.015	4.943	.495
sesbinnedla * schbinLA	.313	4	.078	1.691	.152	.021	6.764	.517
Error	14.632	316	.046					
Total	312.787	326						
Corrected Total	39.885	325						

a. R Squared = .633 (Adjusted R Squared = .623)
b. Computed using alpha = .05

Analogous to what was executed in the first factorial ANOVA, the chart (See Figure 12) illustrated the plots of the estimated marginal means of the dependent variable, TPLA_Reflext, for the SCHDAYL groups and shown separately by SES bin while controlling for student attendance. The position of the line segments on this chart were almost identical to those presented on the first factorial ANOVA. Therefore, even when controlling for differences in student attendance rates between school categories, the poor schools performed significantly lower than the median schools and the median schools performed significantly worse than the wealthier schools on the HSPA LA. On the other hand, when the attendance factor (G11attend, the covariate) was introduced, the shapes of the lines for each SES category changed. For the poor schools there was little change in the HSPA LA passing percentage when going from a short day to a median day, but significant improvement in the HSPA LA passing rates existed when going from a median to a long day. In contrast, for both the median and wealthy schools, there was little change in the HSPA LA passing percentage when the school day length went from short to median as well as from median to long when the passing percentages were adjusted for differences in student attendance.

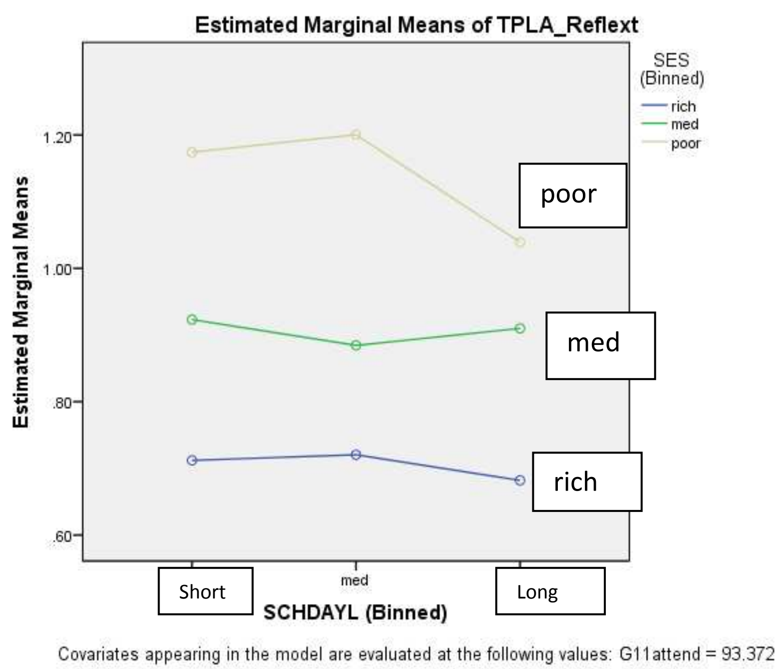


Figure 11. LA Estimated Marginal Means (Second Factorial ANCOVA) Transformed Dependent Variable (TPLA_Reflext) with Binned SCHDAYL and SES with Covariate G11attend

Univariate Analysis Non-Transformed Dependent Variable LA

A third factorial ANOVA was constructed using the same SES and SCHDAYL binned groups along with G11attend as a covariate. However, in this factorial ANCOVA (See Table 56) the original dependent variable (TP+AP) was used rather than the transformed dependent variable (TPLA_Reflext). The descriptive statistics showed the mean HSPA LA passing percentage as well as the standard deviation of the passing percentages for each combination of SCHDAYL bin and SES bin. Note that the descriptive table showed actual data with no adjustments for the G11attend covariate. An examination of this table showed that for both the rich and median SES schools lengthening the school day from a short day to a median day as well as from a median day to a long day had little if any impact on HSPA LA passing rates. For the poor schools, going from a short day to a median school day had little impact on the HSPA LA passing percentage; but going from a median school day to a longer day increased the HSPA LA passing percentage by about almost three points.

Table 56

LA Descriptive Statistics Untransformed Dependent Variable (TP+AP)

Dependent Variable: TP+AP

SCHDAYL (Binned)	SES (Binned)	Mean	Std. Deviation	N
short	rich	96.226	2.1060	27
	med	91.740	4.9170	45
	poor	78.828	12.6652	43
	Total	87.965	11.0779	115
med	rich	95.828	2.9215	46
	med	93.129	3.6949	38
	poor	78.036	15.2510	28
	Total	90.464	10.8585	112
long	rich	96.914	1.3400	36
	med	92.958	3.5586	26
	poor	80.792	15.8830	37
	Total	89.849	12.1824	99
Total	rich	96.285	2.3297	109
	med	92.515	4.2295	109
	poor	79.295	14.4155	108
	Total	89.396	11.3687	326

The test of between-subjects effects for this third factorial ANOVA (See Table 57) presented a significant difference in the dependent variable (TP+AP) for the three SES groups $F(2, 316) = 43.3$, $p = .001 < .05$. Nevertheless, there were no significant differences between the three SCHDAYL groups $F(2, 316) = .53$, $p = .591 > .05$. Similar to what was reported previously on the transformed scores, the untransformed scores revealed no significant interaction between the SES groups and SCHDAYL groups $F(4, 316) = 1.01$, $p = .402 > .05$.

Table 57

LA Tests of Between-Subjects Effects (Third Factorial ANOVA) Untransformed Variable (TP+AP)

Dependent Variable: TP+AP

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	27902.713[a]	9	3100.301	69.468	.000	.664
Intercept	2926.248	1	2926.248	65.568	.000	.172
schbinLA	46.955	2	23.477	.526	.591	.003
sesbinnedla	3864.998	2	1932.499	43.301	.000	.215
schbinLA * sesbinnedla	180.319	4	45.080	1.010	.402	.013
G11attend	10443.604	1	10443.604	234.008	.000	.425
Error	14102.872	316	44.629			
Total	2647282.510	326				
Corrected Total	42005.585	325				

a. R Squared = .664 (Adjusted R Squared = .655)

The estimated marginal means exposed each SCHDAYL/SES bin combination mean passing percentage, after controlling for differences in student attendance rates, among the schools included in the study (See Table 58). Even when controlling for differences in student attendance rates, the length of the school day had little influence on HSPA LA passing percentages for the both rich schools and median SES schools. In contrast, for the poor schools lengthening the school day from a short to a median length actually resulted in a slight reduction of the HSPA LA passing rate by 2.5 percentage points. On the other hand for poor schools, increasing the school day from a median length to a long length day resulted in a rise of about 3.5 percentage points in the passing rate on HSPA LA. When one compares the HSPA LA performance on poor schools with a short day versus those of a long day there was about a one percentage point improvement in the passing rate.

Table 58

LA Estimated of Marginal Means Untransformed Dependent Variable (TP+AP) with Binned SCHDAYL and SES with Covariate G11attend

Dependent Variable: TP+AP

SCHDAYL (Binned)	SES (Binned)	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
short	rich	92.855[a]	1.304	90.288	95.421
	med	91.936[a]	.996	89.977	93.896
	poor	84.154[a]	1.077	82.035	86.272
med	rich	93.070[a]	1.001	91.100	95.040
	med	91.509[a]	1.089	89.367	93.652
	poor	81.676[a]	1.285	79.148	84.204
long	rich	92.366[a]	1.152	90.098	94.633
	med	90.914[a]	1.317	88.323	93.505
	poor	85.023[a]	1.133	82.794	87.251

a. Covariates appearing in the model are evaluated at the following values: G11attend = 93.372.

Figure 12 displayed the plots of the estimated marginal means of the dependent variable, TP+AP, for the SCHDAYL shown separately by SES bin. The marginal means were adjusted to control for differences in student attendance rates between schools. The line segments for the poor, median, and rich schools were separate and distinct, which clearly confirmed that there were significant differences in HSPA LA performance between these three types of schools. Since we used the actual dependent variable, TP+AP, the order of the line segments showed that the poor schools performed significantly lower than the median and the wealthy schools on the HSPA LA. Comparing the wealthy schools to the median schools, the wealthy schools performed better than the median schools, but the difference in performance was much smaller between either of these SES groups and the poor schools. Looking at the rich schools there was little to no change in the HSPA LA passing percentage as the school day was lengthened from a short to a median school day and from a median to a long school day. For the median SES schools, there was a very slight decline in the passing percentage (less than 1%) from a short to a median day length as well as from a median to a long day length. Last, for the poor schools there was a decline in the HSPA LA passing percentage when the school day length increased from a short day to a median day, but this decline was reversed when the school day was

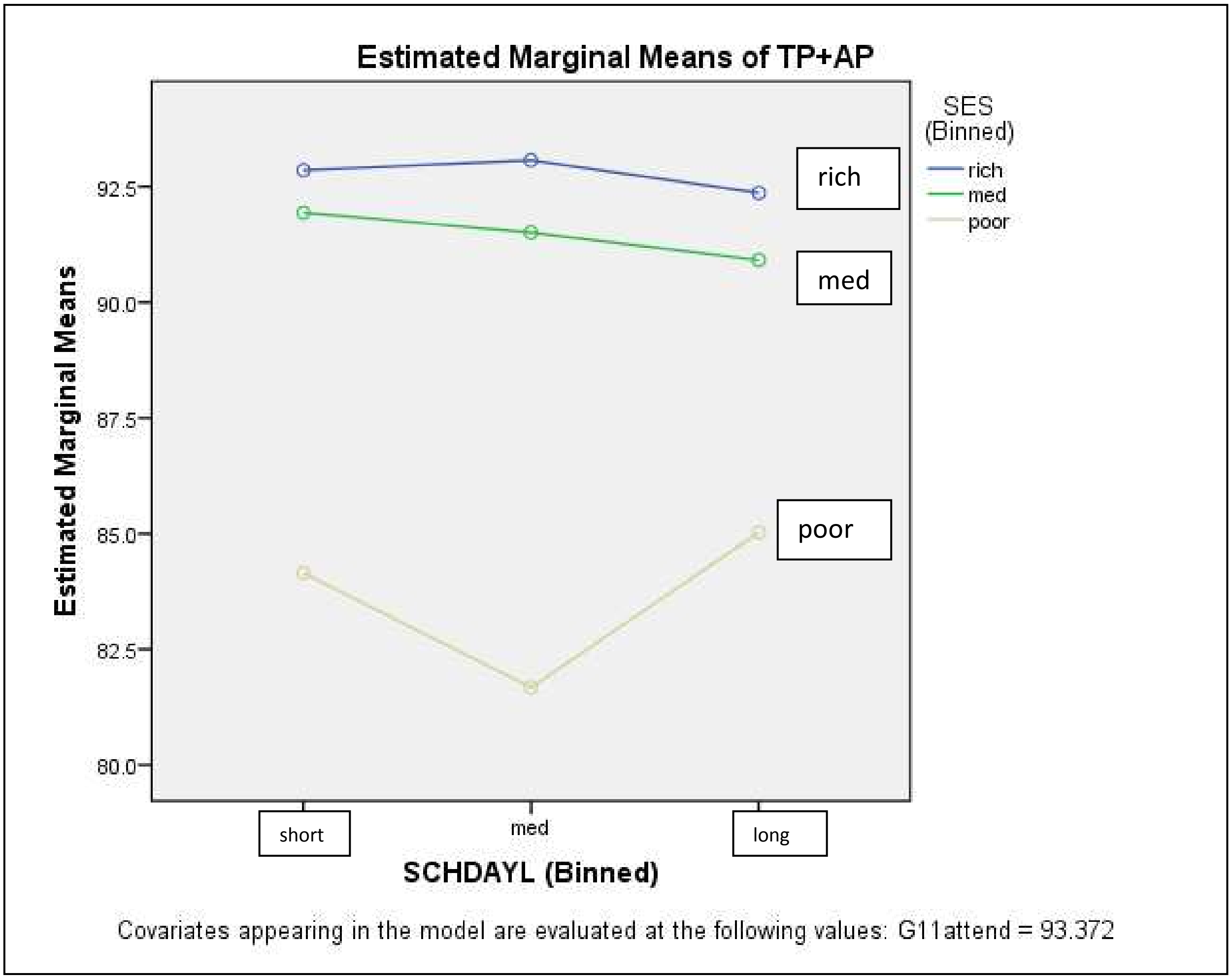


Figure 12. LA Estimated Marginal Means Untransformed (TP+AP) with Binned SCHDAYL and SES with Covariate G11attend

Overall Conclusions

The final hierarchical regression models (when using the transformed dependent variable) for both MA and LA had significant predictive capabilities on the HSPA passing rates. The fact that the adjusted R^2 of 64.0% for LA was about five percentage points higher than the MA adjusted R^2 of 58.7% showed that the LA regression model had slightly higher predictive power than the MA model.

Both MA and LA socioeconomic status (SES) had the greatest influence on HSPA passing percentages; the extant literature supports this outcome. This was demonstrated by the fact that SES had the largest R^2 value contribution—43.1% for MA and 48.1% for LA—in each subject's final regression model. Unfortunately, SES is a variable that schools have little power to change and hence the predictive powers of other more mutable variables need to be examined.

In this study, the other significant variables for MA included G11attend, SCHDAYL, and MA+, while for LA the significant variables were G11attend, SCHDAYL, DIS, MA+, and enrG9to12. Out of these variables the ones that schools and administrators have some ability to change include G11attend, SCHDAYL, MA+, and enrG9to12. While some school districts might be able to reduce the number of special education (DIS) students housed in regular high schools, this cannot always occur because of public policy, budgetary, legal, and other constraints. In determining which of these variables have the greatest influence, schools and administrators and other stakeholders should recognize the contribution that each of these variables has on HSPA performance.

After SES, G11attend (student attendance) had the highest R^2 value contribution to the HSPA passing percentage rate at about 10% for both subjects. This was followed by school day length, which had a 5.7% contribution for MA and a 3.4% contribution for LA. The percentage of faculty with master's degrees or better had only about a one percent contribution to the HSPA passing rates. For LA the high school size (enrG9to12) had about a .5% contribution. In summary, these results suggest that out of all these mutable variables the focus should be on improving student attendance, perhaps followed by initiatives to lengthen the school day.

When analyzing the above results, one must remember that a transformed dependent variable—which involved both a reversal of the scores and a non-linear (i.e., log10) transformation of the scores—was used in all regression analyses. The problem with using a transformed variable was the difficulty in determining the actual percentage point effect on the HSPA passing rates for each of the predictor variables.

To partially compensate for this issue, factorial ANOVAs were run for both MA and LA, using the original dependent variable TP+AP. In the factorial ANOVAs, three SES and three SCHDAYL bins were used in order to divide the schools into approximately equal-sized groups based on the values of each of these predictors. Two variables, SES and SCHDAYL, were chosen for binning purposes because they were among the most significant variables in both the MA and LA regression analyses. In addition, for both MA and LA, G11attend was selected as a covariate because student attendance was also found to be a significant predictor variable.

In the MA factorial ANOVA, significant differences were found in the HSPA passing percentages among the SES bins but not among the SCHDAYL bins. Further analysis showed that for the median and wealthy SES schools there was little variation in the MA passing percentages when the length of the school day was increased. While there was little difference in the HSPA passing rate for poor schools (low SES) when the school day was lengthened from a short day to a median day, there was a 6 point improvement when the school day was increased from a median to a long day.

Similarly for LA, the factorial ANOVA found significant differences in the HSPA passing percentages among the SES bins but not among the SCHDAYL bins. Subsequent analysis showed that for the median and wealthy SES schools there was little variation in the LA passing percentages when the length of the school day was increased. For the poor schools the

LA passing rate declined from a short to a median length day but improved about 3.5 points when the school day was increased from a median to a long day.

The Null Hypotheses

The researcher rejects the null hypotheses and concludes that there is a statistically significant relationship between the school day length predictor variable and the 2011 Grade 11 NJ HSPA Mathematics for the 326 New Jersey high schools as measured by Proficient or above.

The researcher rejects the null hypotheses and concludes that there is a statistically significant relationship between the school day length predictor variable and the 2011 Grade 11 NJ HSPA Language Arts passing percentage.

The decisions to reject the null hypotheses were based on the statistical analyses performed and discussed in Chapter IV. The majority of these analyses were multiple linear regressions using a transformed dependent variable and a set of predictor variables. In all of these regressions, school day length was found to be a statistically significant predictor variable. As measured by the standardized betas, the strength and direction of the relationships between the school day predictor variable and the transformed dependent variable were found to be small to median-sized negative relationships (-.23 for MA and -.18 for LA). Since the transformed dependent variable involved a reversal of scores, this implies that school day length had a small to median strength positive relationship with the original dependent variable (the actual HSPA passing percentage) for both subjects.

Factorial ANOVAs were also run for each subject (MA and LA), using the transformed predictor variable as well as two grouping variables with three levels each based on the percentage of SES students and the length of the school day, respectively. For each subject one factorial ANOVA was run without any covariates and another was run using student attendance

(G11attend) as a covariate. For both MA and LA, both of these factorial ANOVAs showed that there were significant differences in the transformed dependent variable between the school day length groups. These results also support rejecting the null hypotheses.

When analyzing the above results, one must remember that a transformed dependent variable—which involved both a reversal of the scores and a non-linear (i.e., log10) transformation—was used in the regression analyses as well the two factorial ANOVAs. The problem with using a transformed variable was the difficulty in determining the actual percentage point impact of the HSPA passing rate for each of the predictor variables.

Factorial ANOVAS Using the Untransformed Dependent Variable (TP+AP)

In order to ascertain the actual percentage points that affect HSPA passing rates, factorial ANOVAs were run (for both MA and LA), using the original dependent variable TP+AP. The factorial ANOVAs used three SES and three SCHDAYL bins in order to divide the schools into approximately equal-sized groups based on the values of each of these predictors. The two variables SES and SCHDAYL were chosen for binning purposes because they were among the most influential variables in both the MA and LA regression analyses. In addition, for both MA and LA, G11attend was selected as a covariate because student attendance was also found to be a significant predictor variable.

For both MA and LA, factorial ANOVAs run using the original dependent variable found no significant differences in the HSPA passing percentages among the school day length bins. These results suggested that in order to get a better understanding of the influence of the school day on the HSPA passing percentages, further analyses needed to be performed using the original untransformed dependent variable. In particular, we would like to determine how the increase in the school day by each additional minute contributes to the passing percentages.

To help answer this question, regression models were run using the original dependent variable (TP+AP) for both MA and LA.

As a first step for each subject, a simultaneous regression model was run by using all the predictor variables in our data base other than STMOB and LEP since these variables were previously identified as having significant correlations with other predictor variables. The purpose of this step was to determine which variables had a significant influence (i.e., had a *p*-value of less than .05) on the dependent variable.

The variables found to have such an influence for MA included G11attend, SES, and SCHDAYL. Next, a hierarchical regression was run using only these three predictor variables. The results of this regression for MA appear in Table 59. As shown in the ANOVA Table 59 the results for Model 3 were significant $F(3,322) = 245.47$, $p = .0001 < .05$.

Table 59

MA ANCOVA[a] Untransformed Dependent Variable (TP+AP) with G11attend

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	61582.252	1	61582.252	377.442	.000[b]
	Residual	52862.776	324	163.157		
	Total	114445.028	325			
2	Regression	77539.064	2	38769.532	339.310	.000[c]
	Residual	36905.964	323	114.260		
	Total	114445.028	325			
3	Regression	79627.500	3	26542.500	245.471	.000[d]
	Residual	34817.528	322	108.129		
	Total	114445.028	325			

a. Dependent Variable: TP+AP

b. Predictors: (Constant), SES

c. Predictors: (Constant), SES, G11attend

d. Predictors: (Constant), SES, G11attend, SCHDAYL

The MA Model Summary (See Table 60) showed that the Model 3 regression had an adjusted R^2 of 69.3%, which means that 69.3% of the variation of the original dependent variable is explained by the model. The R^2 change column of the model summary revealed that using the length of the school day as an independent variable to predict the dependent variable of student 2011 NJ HSPA mathematics passing percentage accounted for 1.8% of its variance.

Table 60

MA Model Summary[d] Untransformed Dependent Variable (TP+AP)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.734[a]	.538	.537	12.7733	.538	377.442	1	324	.000	
2	.823[b]	.678	.676	10.6892	.139	139.654	1	323	.000	
3	.834[c]	.696	.693	10.3985	.018	19.314	1	322	.000	1.583

a. Predictors: (Constant), SES

b. Predictors: (Constant), SES, G11attend

c. Predictors: (Constant), SES, G11attend, SCHDAYL

d. Dependent Variable: TP+AP

The *p*-values of the MA Coefficients (See Table 61) confirmed that all three predictor variables were statistically significant. In addition, the unstandardized beta values corresponding to each of the predictor variables in Model 3 explained what a unit increase in each of the independent variables had on the dependent variable. For SCHDAYL (the focus of this study) each minute increase in the length of the school day improves the HSPA MA passing percentage by just under one tenth of a percentage point. Similarly, each one percentage point increase in the G11attend rate increased the HSPA MA passing rate by about 2.3 percentage points. On the other hand, each one percentage point increase in the proportion of SES students by school decreased the HSPA MA passing rate by almost four tenths of a percentage point. In conclusion, out of these three predictor variables, the school day length had the least influence on the HSPA MA passing percentage.

Table 61

MA Coefficients Untransformed Dependent Variable (TP+AP)

		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	87.500	.995		87.927	.000		
	SES	-.505	.026	-.734	-19.428	.000	1.000	1.000
2	(Constant)	-151.167	20.213		-7.479	.000		
	SES	-.349	.025	-.507	-13.733	.000	.732	1.367
	G11attend	2.511	.212	.437	11.818	.000	.732	1.367
3	(Constant)	-173.780	20.325		-8.550	.000		
	SES	-.378	.026	-.550	-14.776	.000	.681	1.468
	G11attend	2.340	.210	.407	11.125	.000	.706	1.415
	SCHDAYL	.096	.022	.140	4.395	.000	.929	1.077

a. Dependent Variable: TP+AP

For LA the results of the simultaneous regression analysis run (See Table 62) using the original TP+AP dependent variable plus all the predictor variables other than STMOB and LEP are shown below. The statistically significant variables (i.e., those with a *p*-value less than .05) in this regression included G11attend, SES, DIS, FATTEND, and FMOBILITY. Note that SCHDAYL was not a statistically significant variable in this regression. This means that lengthening or changing the school day does not have a statistically significant influence on the HSPA LA passing rate. To gain a further understanding of the statistically significant variables, a second regression was run, using only those variables.

Table 62

LA Coefficients Untransformed Dependent Variable (TP+AP)

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	-88.624	13.018		-6.808	.000		
	G11attend	1.973	.146	.566	13.485	.000	.548	1.825
	SES	-.164	.018	-.394	-9.350	.000	.543	1.840
	DIS	-.209	.088	-.086	-2.366	.019	.728	1.373
	FATTEND	-.104	.050	-.071	-2.067	.040	.829	1.207
	FMOBILITY	.152	.069	.073	2.210	.028	.880	1.137
	MA+	-.025	.028	-.031	-.891	.374	.822	1.216
	enrG9to12	.001	.001	.052	1.466	.144	.768	1.302
	SCHDAYL	.020	.014	.047	1.439	.151	.887	1.128

a. Dependent Variable: TP+AP

Overall, the ANOVA (See Table 63) results for LA in the hierarchical regression indicated that the final regression model (Model 5) was statistically significant $F(5,320) = 142.05$, $p = .0001 < .05$.

Table 63

LA ANCOVA Untransformed Dependent Variable (TP+AP) with G11attend Covariate

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	23753.846	1	23753.846	421.672	.000[b]
	Residual	18251.739	324	56.333		
	Total	42005.585	325			
2	Regression	28444.850	2	14222.425	338.761	.000[c]
	Residual	13560.735	323	41.984		
	Total	42005.585	325			
3	Regression	28649.145	3	9549.715	230.227	.000[d]
	Residual	13356.440	322	41.480		
	Total	42005.585	325			
4	Regression	28810.073	4	7202.518	175.212	.000[e]
	Residual	13195.511	321	41.108		
	Total	42005.585	325			
5	Regression	28958.684	5	5791.737	142.053	.000[f]
	Residual	13046.901	320	40.772		
	Total	42005.585	325			

a. Dependent Variable: TP+AP

b. Predictors: (Constant), G11attend

c. Predictors: (Constant), G11attend, SES

d. Predictors: (Constant), G11attend, SES, DIS

e. Predictors: (Constant), G11attend, SES, DIS, FMOBILITY

f. Predictors: (Constant), G11attend, SES, DIS, FMOBILITY, FATTEND

The LA Model Summary (See Table 64) showed that the Model 5 regression had an adjusted R^2 of 68.5%, which means that 68.5% of the variation of the original dependent variable was explained by the model.

Table 64

LA Model Summary[f] Untransformed Dependent Variable (TP+AP)

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.752[a]	.565	.564	7.5055	.565	421.672	1	324	.000	
2	.823[b]	.677	.675	6.4795	.112	111.734	1	323	.000	
3	.826[c]	.682	.679	6.4405	.005	4.925	1	322	.027	
4	.828[d]	.686	.682	6.4115	.004	3.915	1	321	.049	
5	.830[e]	.689	.685	6.3853	.004	3.645	1	320	.057	1.974

a. Predictors: (Constant), G11attend

b. Predictors: (Constant), G11attend, SES

c. Predictors: (Constant), G11attend, SES, DIS

d. Predictors: (Constant), G11attend, SES, DIS, FMOBILITY

e. Predictors: (Constant), G11attend, SES, DIS, FMOBILITY, FATTEND

f. Dependent Variable: TP+AP

The p-values shown for Model 5 for the LA Coefficients (See Table 65) confirmed that four of the five predictor variables were statistically significant. (The only exception was FATTEND, whose *p*-value in this model was a marginally significant .057). As previously explained, the unstandardized beta values corresponding to each of the predictor variables told what a unit increase in each of the independent variables had on the dependent variable. For G11attend each one percentage point increase in the student attendance rate improves the HSPA LA passing percentage by two percentage points. Similarly, each one percentage point increase in the faculty mobility rate increased the HSPA LA passing rate by about .15 percentage points. On the other hand, each percentage point increase in the proportions of DIS and SES students by school decreased the HSPA LA passing rate by 16 hundredths of a percentage point. In conclusion, the predictor variable that had by far the most influence on the HSPA LA passing rate was student attendance with the other significant variables each having a very small influence on the HSPA LA passing percentage.

Table 65

LA Coefficients with Untransformed Dependent Variable (TP+AP) with G11attend Covariate

		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	-155.289	11.923		-13.024	.000		
	G11attend	2.621	.128	.752	20.535	.000	1.000	1.000
2	(Constant)	-79.958	12.519		-6.387	.000		
	G11attend	1.862	.131	.534	14.163	.000	.702	1.424
	SES	-.166	.016	-.399	-10.570	.000	.702	1.424
3	(Constant)	-78.290	12.467		-6.280	.000		
	G11attend	1.846	.131	.530	14.099	.000	.700	1.429
	SES	-.159	.016	-.382	-10.009	.000	.676	1.479
	DIS	-.175	.079	-.072	-2.219	.027	.929	1.077
4	(Constant)	-84.594	12.813		-6.602	.000		
	G11attend	1.907	.134	.547	14.235	.000	.662	1.510
	SES	-.161	.016	-.386	-10.130	.000	.675	1.482
	DIS	-.172	.079	-.071	-2.189	.029	.928	1.077
	FMOBILITY	.135	.068	.065	1.979	.049	.911	1.098
5	(Constant)	-85.076	12.763		-6.666	.000		
	G11attend	2.008	.144	.576	13.988	.000	.572	1.749
	SES	-.159	.016	-.382	-10.067	.000	.673	1.485
	DIS	-.162	.079	-.067	-2.065	.040	.924	1.082
	FMOBILITY	.153	.069	.074	2.234	.026	.893	1.120
	FATTEND	-.095	.050	-.065	-1.909	.057	.841	1.188

a. Dependent Variable: TP+AP

CHAPTER V

CONCLUSIONS AND RECOMMENDATIONS

Introduction

This chapter presents a summary of findings, conclusions, and recommendations for policy and practice as well as implications for future research. The conclusions and recommendations for practice and future research are based on the production-function theory (inputs equal outputs). The results of my study add to the existing base of literature and can help administrators make informed decisions about the factors that influence student achievement and in particular the establishment of effective policies designed to restructure schools around the variable, length of the school day, from the reported effect sizes on the Grade 11, 2011 NJ HSPA high school exit exam in LA and MA. The researcher discussed the quantitative data collected and analyzed in Chapter four.

As part of the Elementary and Secondary Education Act (ESEA) Title I legislation accountability testing began and federal funds were allocated to benefit the education of poor and minority children. Because there has been little increase in student achievement among these groups, an empirical analysis of how the funds have been actually used to benefit these groups must be conducted.

In the year 2012, the State of New Jersey passed legislation entitled Senate No. 2087 which further supplemented chapter 6 of Title 18A related to lengthening the school day and school year; the NJDOE has been running this three-year pilot-program to ascertain whether lengthening the school day will have a positive effect on student achievement (NJ Legislature, 2012). This piece of legislation and subsequent educational policy uses the increase of school time as a lever to improve school and student achievement. However, my research study proved that a blanket overall increase in the length of the school day throughout schools and districts in New Jersey will have little influence on the NJ HSPA exam; a six-point gain in the Math section and hardly any gain in the Language Arts section of the exam does not warrant spending millions of taxpayer dollars. Yet, in Governor Chris Christie's 2014 State of the Union message he belted out, "It is time to lengthen both the school day and school year" (Brody, 2014).

The Star Ledger reported on poverty in New Jersey in 2013 and stated that in 2011 it was at a record 52-year high. Johnson (2013) provided the definition of being poor in New Jersey "as a family of three making less than $37,060. In 2011, 2.1 million New Jersey residents lived in poverty (about 24.7% of the state's population) and that's twice the federal poverty rate because New Jersey's cost of living is among the highest in the nation" (Johnson, 2013, p. 1). Furthermore, Johnson (2013) summarized more facts related to poverty in New Jersey:

- A record high of more than 630,000 children—1.2%—lived in a household defined as poor
- The percentage of 18- to 24-year-olds living in poverty rose from 26.9 in 2007 to 32.8 in 2011
- Of families headed by single mothers, 22% were poor compared to 3.6% of families headed by a married couple
- African-Americans and Hispanics had poverty rates at least three times higher than Whites (p. 1).

Summary of Findings

For both MA and LA, socioeconomic status (SES) had the greatest influence on HSPA passing percentages; the extant literature supports this outcome. This was demonstrated by the fact that SES had the largest R^2 contribution—43.1% for MA and 48.1% for LA—in each subject's final regression model. Unfortunately, SES is a variable that schools have little power to change. Further analysis showed that for the median and wealthy SES schools, there was little variation in the MA passing percentages when the length of the school day was increased. While there was little difference in the MA HSPA passing rate for poor schools (low SES) when the school day was lengthened from a short day to a median day, there was a 6 point improvement when the school day was increased from a median to a long day. Subsequently the analysis in this study showed that for the median and wealthy SES schools, there was little variation in the LA passing percentages when the length of the school day was increased. For the poor schools, the LA passing rate declined from a short to a median length day but improved about 3.5 points when the school day was increased from a median to a long day.

White (1982) affirmed, "The family characteristic that is the most powerful predictor of school performance is socioeconomic status (SES); the higher the SES of the student's family, the higher his academic achievement." "Because of the social, economic, and methodological changes that have occurred since the publication of White's (1982) review, it is difficult to estimate the current state of the relation between SES and academic achievement" (Sirin, 2005, p. 418). Finally, Sirin (2005) asserted that "the magnitude of the SES-school achievement relationship is not as strong as was reported in White's (1982) meta-analysis" (p. 442). Nonetheless, Koretz (2008) suspected that only weak information about SES is ever gathered and therefore "even though the effect of this weak measurement of SES is to make its relationship with scores appear weaker than it ought, we typically find striking differences in performance associated with socioeconomic status” (p. 103).

After SES, G11attend (student attendance) had the highest R^2 contribution to the HSPA passing percentage rate at about 10% for both subjects. This was followed by school day length, which had a 5.7% contribution for MA and a 3.4% contribution for LA. Many researchers have confirmed that student attendance has a statistically significant relationship with student achievement on standardized tests, particularly for Math (Balfanz, & Byrnes, 2006, 2012; Gottfried, 2010)). My study supports the findings in the extant literature that there is a “positive and statistically significant relationship between student attendance and academic achievement” (Gottfried, 2010).

Recommendations for Policy

As mentioned in Chapter II of my literature review in this study, Coleman et al. (1966) reported that socioeconomic status (SES) had the greatest influence on student achievement. However, Coleman et al. (1966) offered a solution to education on this topic: to integrate schools based on socioeconomic status. He found that peers from mixed socioeconomic backgrounds, especially those from wealthier backgrounds, would be good academic role models and positively influence those from more disadvantaged backgrounds. His research also uncovered no negative academic impact on students from the wealthier backgrounds attending school side by side with the disadvantaged. “In 1966, the Coleman report argued that variables associated with students' homes, rather than with school, accounted for a significant share of student success” (Coleman et al., 1966, as cited by Mattingly, Prislin, McKenzie, Rodriguez and Kayzar, 2002, p. 552). Yet, since 1966 state and federal governments have not acknowledged this nor passed legislation to support this finding.

A change in educational policy that addresses the margin of error surrounding standardized tests would certainly be more helpful to students of poverty, who may be denied a high school diploma because political and educational pundits refuse to acknowledge this technical phenomenon. Tienken (2011) found conditional standard error of measure (CSEM) of about 10 points on the NJ HSPA test. Tienken (2011) found a technical interpretation flaw he calls "conditional standard error of measurement (CSEM)" (p. 301) in the construct validity of high school exit exams/high-stakes tests. That translates into the fact that there is a margin of error on all these tests which can, for example, result in ±10 points from a student's individual true scale score. That means that many students may in fact pass the high-stakes test but be categorized as failing and therefore be prevented from graduating from high school. Furthermore, Tienken (2011) suggested that adjustment to policy should be made to ameliorate the impact of CSEM on a single test score that determines the fate of students and families.

> Because high school exit exams and CSEM are nationwide phenomena, perhaps hundreds of thousands of students might have been potentially negatively affected in the *NCLB* era by what appears as inaction at the state and national levels to develop policy remedies aligned with standards and recommendations for appropriate testing practices (Tienken, 2011, p. 310).

"In the 2009-2010 school year, states that administered high school exit exams enrolled 74% of all students and 83% of students of color" (Center on Education Policy, 2010, as cited by Shuster, 2012, p. 3). The cost attached to exit exams comes high. The NJDOE contracts with Measurement, Inc. to handle the HSPA exit exam and will pay them $19.5 million over two and half years until 2015 to continue their contract (Mooney, (2012). California's 2003-2004 budget included $21 million for the administration of the California High School Exit Examination (CAHSEE), (Shuster, 2012, p. 3).

Recommendations for Practice

Many factors influence student achievement and although SES is touted as the strongest predictor (particularly related to standardized tests), one cannot ignore that the "lack of cooperation among schools, parents, and their communities has also been found to play a role in student achievement" (Scribner, Young, & Perdroza, l999, as cited by Marschall, 2006, p. 1054). Schools, particularly in lower socioeconomic areas, must assess the needs of their communities and provide services that help address those requirements. Marketing plans that reach out to the parents of students through community efforts requires a change in thinking about the population being served. For example, introducing simple strategies accompanied by technology training for parents could include (a) a Wi-Fi pop up that would appear on a parent cell phone so that they might log into their child's academic and attendance record the moment they are on school grounds, (b) security personnel or other appropriate staff member(s) could also be stationed outside school buildings so that when parents come to drop off or pick up their child, school personnel can train them in using their cell phones to access student records.

School principals need to be proactive in finding ways to build relationships and educate families in poorer districts (minimizing the role that parent involvement may play in student achievement at the high school level is risky); one way is through support of out of school time programs (OST).

> Out of School Time (OST) programs are ones that provide staff with the opportunity to build relationships with families by communicating frequently, and in ways that welcome families to initiate contact, and by showing families that

staff are there for them" (Kakli, Kreider, Little, Buck, & Coffey, 2006, p. 11). Furthermore, "research shows that families are more likely to be involved when staff reach out to them and also when they feel that their involvement is appropriate and will be effective" (Hoover-Dempsey & Sandler, 1997; Moll, Amanti, Neff, & Gonzalez, 1992, as cited by Kakli et al. p. 11).

Westmoreland (2011) reported on OST programs; these programs have gained attention because they have a federal, state and local funding component.

- Interest in OST has increased for several reasons. The three primary reasons are that the majority of students' parents are employed outside the home, pressure has increased to improve student achievement at many schools, and communities express concerns regarding students' undesirable afterschool activities.
- The 21st Century Community Learning Centers, serving approximately 6.5 million children and youth across the United States, report waiting lists for many of these programs.
- OST programs spend funds on family literacy and other engagement activities. As schools and school districts consider ways to align and coordinate their services, fostering family engagement in OST programs emerges as a key strategy that can then lead to better engagement at home and at school. (Westmoreland, 2011 pp. vii, viii, 4).

For learning to occur, especially for students in low-income designated strata, students need to attend school and be in class learning (Gottfried, 2010). The analyses in my study showed a significant and positive relationship between student attendance and academic achievement. Therefore, more focus on attendance policies that have the potential to positively influence HSPA passing percentage rates should gain administrative focus, including greater awareness on the part of the parent about the importance of students being in the classroom. Children have to attend school in order to learn; chronic absenteeism for any child for any reason is detrimental to their ongoing development but even more profound for younger children of poverty. The subject of math is particularly sensitive to student attendance and researchers reported that students with better attendance records, especially those of poverty, have stronger test performance (Balfanz & Byrnes, 2006, 2012; Lamdin, 1996; Nichols, 2003).

When a student misses class time, for schedule changes or for any other reason, the missed time negatively affects academic achievement. Research consistently showed that more instructional time led to higher achievement (Dreeben & Gamoran, 1986, cited by Kubitschek, Hallinan, Arnett, Galipeau, 2005; Karweit & Slavin, 1981; Wiley, 1976). Principals can increase accountability for non-instructional time at the local level.

> Without time available for the teaching of academic material, students will not be exposed to such material and therefore will be unable to learn it. For this reason, school policies that decrease the amount of time available for teaching and learning should be discouraged (Kubitschek et al., 2005, p. 63).

Conclusions

Clearly, based on the literature reviewed, research and statistical analyses conducted in this study indicate that the most significant factors that influence the percentage passing rates on the NJ HSPA are out of the purview of teachers and administrators. Socioeconomic status is a societal problem beyond the scope of school leaders.

According to Arnold (2014), the cost of an extended school day schedule "on average is estimated at $1,200 extra per student. Massachusetts is spending about $1,300 per student extra on its extended school day" (p. 1). On the low side that translates into approximately $2 million dollars per year per school just to cover teacher salaries. Yet, according to Schachter (2014):

- Still, some studies have questioned whether extended learning time yields enough "bang for the buck." The National Academy of Education in Washington recently found that by its calculations, every 10% increase in time has resulted in just a 2% jump in actual learning.
- "There's no sugarcoating the fact that it takes resources," says the Center for American Progress's Owen, who estimates that providing 300 extra hours in learning time will increase school budgets by 6% to 20%, depending on the staffing model (Schachter, 2014, p. 1).

Because of the significant expense in lengthening the school day for all schools, policies and practices should be more focused on creating strategies that improve student attendance rates, which was a significant finding in this study. Parental education and parental involvement programs can help to improve attendance rates. Missed class time within the high school day is not tracked. Students are known to miss class time for assemblies, field trips, testing, college interviews, public service (i.e., reading to children in lower grades), sports events, rehearsals or actual musical/theatrical or other programs, guidance counselor or discipline meetings, missed time due to schedule changes, in-school and out-of-school suspensions as well as a host of other events. This missed class time (non-instructional time) needs to be controlled and tracked by administration so that student learning is not negatively impacted (Aaronson et al., 1998).

"The literature has lauded parental involvement as an effective strategy to increase student achievement, but schools still struggle with how to effectively involve parents of color and low-income families" (Bower & Griffin, 2011, p. 77). Note that "the gap between the desired and actual levels of parent involvement has led to a wealth of literature and strategies developed for schools" (Bower & Griffin, 2011, p. 77). Deslandes (2005) confirmed that, "parent involvement appears to have lasting benefits even through high school" (p. 164). Unfortunately, when it comes to secondary public education, there is a dearth of specific research and knowledge about parental involvement programs.

The typical factors that repeat in the literature to inform us about what influences the level and motivation of parent involvement included the following: "culture, language, income level, education level, family structure, family size, parent gender, work outside the home and child characteristics (e.g. age, gender, grade level, academic performance)" (Deslandes, 2005, p. 164). Although these typical barriers are known, we must find a way to overcome them. One significant finding in Deslandes (2005) was that "parents will become involved if they perceive that their young children or adolescents want them to do so" (p. 165).

Students that are at risk, those identified as having poor math or language arts skills, need early interventions to target specific skill deficiencies. "For the high concentrations of minority students attending high-poverty urban schools, as well as for the nation as a whole, low mathematical proficiency at the end of the eighth grade has serious consequences" (Balfanz & Byrnes, 2006, p. 144). Providing blanket non-specific math courses or adding more time to the school day that does not target specific skills will not improve the academic achievement of students. Math or language arts workshops should be a curriculum choice that a guidance counselor adds to a student's schedule so that specific skill deficiencies can be addressed for the student that needs the support rather than filling up schedules with electives or trying to address deficiencies in required classes.

Recommendations for Future Research

This research adds to the extant literature on the influence of the length of the school day and student achievement on the NJ HSPA. Obviously a single study cannot relate all the elucidations that influence student achievement on a state's exit exam. However, the variables examined in this study were taken from the NJ School Report Card and do provide a direction for further research and information that can be used at the local district level. The results of this study were supported in the extant literature by the factors identified as influencing student achievement. Nevertheless, this study focused solely on public high schools in one state; therefore, to add more to the extant literature on the topic about the influence of the length of the school day on student achievement on high school exit exams future research on the following topics is suggested:

1. Re-create this study in other states and at the national level and compare the findings.
2. Design an experimental study to examine the instructional day and student achievement.
3. Design a study to examine the actual minutes used for non-instructional purposes in high schools (e.g. assemblies, field trips, guidance counselor meetings, and sundry other reasons students are pulled from classroom instructional time).
4. Conduct a study on the academic achievement of high school students with high absenteeism rates in New Jersey high schools.
5. Conduct a study on the academic achievement of high school students with high tardiness rates in New Jersey high schools.
6. Design a study that closely examines high school students in New Jersey who have not passed the NJ HSPA exam.

7. Conduct a study on how Title I funds have been used and the academic benefit derived for those in the demographic groups that received the funding.
8. Design a study on teacher and administrative perceptions of the length of the school day and student academic achievement.
9. Conduct a study on the early academic interventions for students who score low on state standardized tests in math and language arts in the freshman and sophomore high school years.
10. Conduct a study to compare the curriculum and academic interventions among schools with the highest and lowest school day lengths.
11. Conduct a study of the schools with the highest and lowest poverty rates and compare the curriculum and academic interventions for students identified as scoring low on standardized tests.
12. Conduct a study that examines New Jersey district and high school policies surrounding what constitutes excused and unexcused absences and the correlation to high school exit exam passing rates.
13. Design a study that examines the influence of parent involvement at the high school level on the passing rates of the HSPA.

We cannot let politicians or federal and local governments implement and influence educational policies that will not lead to increased student growth and academic achievement. Educators must speak out publicly and do the right thing locally to improve the education of each child. We all must heed the words of John F. Kennedy (1963) and remember that

"Children are the world's most valuable resource and its best hope for the future."

– United States Committee for UNICEF July 25, 1963, John F. Kennedy Presidential Library.

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Appendices

Appendix A. List of Schools in Sample

326 HIGH SCHOOLS IN SAMPLE					
	UniqueID	CO_NAME	DIS_NAME	SCH_NAME	DFG
1	391320405	Union	Elizabeth City	A. Hamilton Prep Acad	A
2	314010025	Passaic	Paterson City	Academy High Sch	A
3	391320402	Union	Elizabeth City	Adm. W. F. Halsey Ldrshp	A
4	133570087	Essex	Newark City	American History High	A
5	133570010	Essex	Newark City	Arts	A
6	250100010	Monmouth	Asbury Park City	Asbury Park High	A
7	010110010	Atlantic	Atlantic City	Atlantic City High	A
8	133570020	Essex	Newark City	Barringer	A
9	110540020	Cumberland	Bridgeton City	Bridgeton High	A
10	070680029	Camden	Camden City	Brimm Medical Arts High	A
11	010590025	Atlantic	Buena Regional	Buena Regional High	A
12	070680030	Camden	Camden City	Camden High	A
13	133570030	Essex	Newark City	Central	A
14	131210150	Essex	East Orange	Cicely Tyson Com Ms/Hs	A
15	070680240	Camden	Camden City	Creative & Prfrmg Arts Hs	A
16	115390090	Cumberland	Vineland City	Cunningham	A
17	271110040	Morris	Dover Town	Dover High	A
18	133570040	Essex	Newark City	East Side	A
19	391320025	Union	Elizabeth City	Elizabeth High	A
20	314010003	Passaic	Paterson City	High School Gov't & Pa	A
21	314010001	Passaic	Paterson City	High School Of Info Tech	A
22	314010035	Passaic	Paterson City	International High	A
23	132330050	Essex	Irvington Township	Irvington High School	A
24	391320401	Union	Elizabeth City	John E. Dwyer Tech Acad	A
25	314010030	Passaic	Paterson City	John F. Kennedy High	A
26	252400010	Monmouth	Keansburg Boro	Keansburg High School	A
27	133570050	Essex	Newark City	Malcolm X Shabazz High	A

	UniqueID	CO_NAME	DIS_NAME	SCH_NAME	DFG
28	175670050	Hudson	West New York Town	Memorial High	A
29	070680305	Camden	Camden City	Met East High School	A
30	233530050	Middlesex	New Brunswick City	New Brunswick High	A
31	133570045	Essex	Newark City	Newark Vocational HS	A
32	133380050	Essex	City Of Orange Twp	Orange High	A
33	313970050	Passaic	Passaic City	Passaic High	A
34	154020050	Gloucester	Paulsboro Boro	Paulsboro High	A
35	334070050	Salem	Penns Grv-Carney's Pt Reg	Penns Grove High	A
36	234090050	Middlesex	Perth Amboy City	Perth Amboy High	A
37	014180050	Atlantic	Pleasantville City	Pleasantville H S	A
38	314010020	Passaic	Paterson City	Rosa Parks Arts High Sch	A
39	334630050	Salem	Salem City	Salem High	A
40	133570055	Essex	Newark City	Science Park High	A
41	391320403	Union	Elizabeth City	T. Jefferson Arts Acad	A
42	391320404	Union	Elizabeth City	T.A. Edison Career/Tech	A
43	133570056	Essex	Newark City	Technology High	A
44	215210050	Mercer	Trenton City	Trenton Central High	A
45	215210051	Mercer	Trenton City	Trenton Central High West	A
46	175240055	Hudson	Union City	Union City High Schl	A
47	133570057	Essex	Newark City	University High	A
48	115390050	Cumberland	Vineland City	Vineland High School	A
49	133570070	Essex	Newark City	Weequahic	A
50	133570080	Essex	Newark City	West Side High	A
51	095790050	Cape May	Wildwood City	Wildwood High	A
52	070680040	Camden	Camden City	Woodrow Wilson High	A
53	394540010	Union	Roselle Boro	Abraham Clark High	B
54	394160051	Union	Plainfield City	Boaacd	B
55	350490020	Somerset	Bound Brook Boro	Bound Brook High	B
56	050600020	Burlington	Burlington City	Burlington City High	B
57	230750030	Middlesex	Carteret Boro	Carteret High	B
58	290770030	Ocean	Central Regional	Central Regional High	B
59	030890030	Bergen	Cliffside Park Boro	Cliffside Park High	B
60	110997030	Cumberland	Cumberland Regional	Cumberland Reg H.S.	B
61	172390075	Hudson	Jersey City	Dr Ronald Mc Nair Acad Hs	B
62	031700050	Bergen	Garfield City	Garfield High	B
63	151730050	Gloucester	Glassboro	Glassboro High	B

	UniqueID	CO_NAME	DIS_NAME	SCH_NAME	DFG
64	071770050	Camden	Gloucester City	Gloucester City Jr Sr H	B
65	011960050	Atlantic	Hammonton Town	Hammonton High	B
66	172060050	Hudson	Harrison Town	Harrison High	B
67	172390050	Hudson	Jersey City	Henry Snyder High	B
68	172390060	Hudson	Jersey City	James J Ferris High	B
69	172410050	Hudson	Kearny Town	Kearny High	B
70	172390082	Hudson	Jersey City	Liberty High School	B
71	172390070	Hudson	Jersey City	Lincoln High	B
72	392660050	Union	Linden City	Linden High	B
73	072670005	Camden	Lindenwold Boro	Lindenwold High School	B
74	032640050	Bergen	Lodi Borough	Lodi High	B
75	252770050	Monmouth	Long Branch City	Long Branch High	B
76	092820050	Cape May	Lower Cape May Regional	Lower Cape May Reg High	B
77	292940040	Ocean	Manchester Twp	Manchester High	B
78	313980010	Passaic	Passaic Co Manchester Reg	Manchester Reg H	B
79	093130050	Cape May	Middle Twp	Middle Twp High	B
80	173610050	Hudson	North Bergen Twp	North Bergen High	B
81	074110010	Camden	Pine Hill Boro	Overbrook High School	B
82	054050055	Burlington	Pemberton Twp	Pemberton Twp High	B
83	414100050	Warren	Phillipsburg Town	Phillipsburg High	B
84	394160050	Union	Plainfield City	Plainfield High	B
85	054450050	Burlington	Riverside Twp	Riverside High	B
86	035430050	Bergen	Wallington Boro	Wallington Jr Sr High Sch	B
87	172390080	Hudson	Jersey City	William L Dickinson High	B
88	155860050	Gloucester	Woodbury City	Woodbury Jr-Sr High	B
89	011790040	Atlantic	Greater Egg Harbor Reg	Absegami H S	CD
90	334150040	Salem	Pittsgrove Twp	Arthur P Schalick H S	CD
91	290185030	Ocean	Barnegat Twp	Barnegat High School	CD
92	170220020	Hudson	Bayonne City	Bayonne High	CD
93	130250020	Essex	Belleville Town	Belleville Sr. High	CD
94	150860030	Gloucester	Clayton Boro	Clayton High	CD
95	310900030	Passaic	Clifton City	Clifton High	CD
96	154940050	Gloucester	Delsea Regional H.S.Dist.	Delsea Regional High Sch	CD
97	151100040	Gloucester	Deptford Twp	Deptford Twp High	CD
98	011310005	Atlantic	Egg Harbor Twp	Egg Harbor Twp H S	CD
99	151715050	Gloucester	Gateway Regional	Gateway Reg High School	CD
100	031860050	Bergen	Hackensack City	Hackensack High	CD

	UniqueID	CO_NAME	DIS_NAME	SCH_NAME	DFG
101	030745050	Bergen	Carlstadt-East Rutherford	Henry P Becton Reg H S	CD
102	392190050	Union	Hillside Twp	Hillside High	CD
103	252430050	Monmouth	Keyport Boro	Keyport High	CD
104	353000050	Somerset	Manville Boro	Manville High	CD
105	053010030	Burlington	Maple Shade Twp	Maple Shade High	CD
106	031345050	Bergen	Elmwood Park	Memorial Sr. High	CD
107	253510050	Monmouth	Neptune Twp	Neptune High School	CD
108	373590050	Sussex	Newton Town	Newton High	CD
109	011790050	Atlantic	Greater Egg Harbor Reg	Oakcrest H S	CD
110	033910050	Bergen	Palisades Park	Palisades Park Jr-Sr High	CD
111	074060050	Camden	Pennsauken Twp	Pennsauken High	CD
112	334075050	Salem	Pennsville	Pennsville Memorial H	CD
113	394290050	Union	Rahway City	Rahway High	CD
114	234830030	Middlesex	South Amboy City	South Amboy High	CD
115	234920050	Middlesex	South River Boro	South River High	CD
116	175580050	Hudson	Weehawken Twp	Weehawken High	CD
117	153280050	Gloucester	Monroe Twp	Williamstown High	CD
118	075820010	Camden	Winslow Twp	Winslow Twp High School	CD
119	070150010	Camden	Audubon Boro	Audubon High	DE
120	410280020	Warren	Belvidere Town	Belvidere High	DE
121	130410020	Essex	Bloomfield Twp	Bloomfield High	DE
122	030440020	Bergen	Bogota Boro	Bogota Jr./Sr. High Sch	DE
123	290530020	Ocean	Brick Twp	Brick Twp High	DE
124	290530025	Ocean	Brick Twp	Brick Twp Memorial High	DE
125	270630020	Morris	Butler Boro	Butler High	DE
126	235850020	Middlesex	Woodbridge Twp	Colonia High	DE
127	392420010	Union	Kenilworth Boro	David Brearley High Sch	DE
128	031370040	Bergen	Englewood City	Dwight Morrow High	DE
129	211430050	Mercer	Ewing Twp	Ewing High	DE
130	051520050	Burlington	Florence Twp	Florence Twp Mem High	DE
131	411870050	Warren	Hackettstown	Hackettstown High	DE
132	312100050	Passaic	Hawthorne Boro	Hawthorne High	DE
133	252120050	Monmouth	Henry Hudson Regional	Henry Hudson Reg School	DE
134	372165030	Sussex	High Point Regional	High Point Regional H S	DE
135	070390020	Camden	Black Horse Pike Regional	Highland High	DE
136	292360025	Ocean	Jackson Twp	Jackson Liberty High	DE
137	292360020	Ocean	Jackson Twp	Jackson Memorial High	DE
138	235850040	Middlesex	Woodbridge Twp	John F Kennedy Mem H	DE
139	292480020	Ocean	Lacey Twp	Lacey Twp High	DE

	UniqueID	CO_NAME	DIS_NAME	SCH_NAME	DFG
140	032860050	Bergen	Lyndhurst Twp	Lyndhurst High	DE
141	012910050	Atlantic	Mainland Regional	Mainland Reg H S	DE
142	053690050	Burlington	Northern Burlington Reg	N Burl Co Reg High School	DE
143	294190010	Ocean	Plumsted Twp	New Egypt High Sch	DE
144	033600050	Bergen	North Arlington Boro	North Arlington High	DE
145	353670050	Somerset	North Plainfield Boro	North Plainfield H	DE
146	093780050	Cape May	Ocean City	Ocean City High	DE
147	053920050	Burlington	Palmyra Boro	Palmyra High	DE
148	313990050	Passaic	Passaic Valley Regional	Passaic Valley High Sch	DE
149	054320050	Burlington	Rancocas Valley Regional	Rancocas Valley Reg H	DE
150	252105050	Monmouth	Hazlet Twp	Raritan High School	DE
151	034370050	Bergen	Ridgefield Boro	Ridgefield Memorial High	DE
152	034380050	Bergen	Ridgefield Park Twp	Ridgefield Park Jr Sr Hs	DE
153	394550050	Union	Roselle Park Boro	Roselle Park High	DE
154	034610050	Bergen	Saddle Brook Twp	Saddle Brook Mid/High Sch	DE
155	174730050	Hudson	Secaucus Town	Secaucus High	DE
156	294950050	Ocean	Southern Regional	Southern Reg High	DE
157	234970040	Middlesex	Spotswood Boro	Spotswood High	DE
158	075035050	Camden	Sterling High School Dist	Sterling High School	DE
159	070390030	Camden	Black Horse Pike Regional	Timber Creek High	DE
160	295190030	Ocean	Toms River Regional	Toms River High East	DE
161	295190040	Ocean	Toms River Regional	Toms River High North	DE
162	295190050	Ocean	Toms River Regional	Toms River High South	DE
163	070390050	Camden	Black Horse Pike Regional	Triton High	DE
164	395290050	Union	Union Twp	Union Senior High	DE
165	375435060	Sussex	Wallkill Valley Regional	Wallkill Valley Reg H S	DE
166	234660050	Middlesex	Sayreville Boro	War Memorial High	DE
167	155620050	Gloucester	West Deptford Twp	West Deptford High	DE
168	055805053	Burlington	Willingboro Twp	Willingboro High	DE
169	235850050	Middlesex	Woodbridge Twp	Woodbridge High	DE
170	390850005	Union	Clark Twp	Arthur L. Johnson H S	FG
171	030300020	Bergen	Bergenfield Boro	Bergenfield High	FG
172	270450020	Morris	Boonton Town	Boonton High	FG
173	050475050	Burlington	Bordentown Regional	Bordentown Reg H S	FG
174	050620010	Burlington	Burlington Twp	Burlington Twp High	FG
175	050840030	Burlington	Cinnaminson Twp	Cinnaminson High School	FG
176	150870020	Gloucester	Clearview Regional	Clearview Reg High Sch	FG
177	070940030	Camden	Collingswood Boro	Collingswood Sr High	FG
178	051060005	Burlington	Delran Twp	Delran High	FG
179	031130040	Bergen	Dumont Boro	Dumont High	FG

	UniqueID	CO_NAME	DIS_NAME	SCH_NAME	DFG
180	231140040	Middlesex	Dunellen Boro	Dunellen High	FG
181	031550050	Bergen	Fort Lee Boro	Fort Lee High	FG
182	071890050	Camden	Haddon Twp	Haddon Twp High	FG
183	211950050	Mercer	Hamilton Twp	Hamilton East-Steinert	FG
184	211950055	Mercer	Hamilton Twp	Hamilton North-Nottingham	FG
185	211950060	Mercer	Hamilton Twp	Hamilton West-Watson	FG
186	032080050	Bergen	Hasbrouck Heights Boro	Hasbrouck Heights High	FG
187	172210005	Hudson	Hoboken City	Hoboken High	FG
188	372240030	Sussex	Hopatcong	Hopatcong High	FG
189	152440050	Gloucester	Kingsway Regional	Kingsway Reg High	FG
190	372465050	Sussex	Kittatinny Regional	Kittatinny Reg High	FG
191	312510050	Passaic	Lakeland Regional	Lakeland Reg H	FG
192	253040050	Monmouth	Matawan-Aberdeen Regional	Matawan Reg High	FG
193	233140050	Middlesex	Middlesex Boro	Middlesex High	FG
194	233290005	Middlesex	Monroe Twp	Monroe Twp High	FG
195	413675050	Warren	North Warren Regional	N Warren Reg High School	FG
196	033550050	Bergen	New Milford Boro	New Milford High	FG
197	233620040	Middlesex	North Brunswick Twp	North Brunswick Twp High	FG
198	133750050	Essex	Nutley Town	Nutley High	FG
199	253810030	Monmouth	Ocean Twp	Ocean Twp High	FG
200	233345040	Middlesex	Old Bridge Twp	Old Bridge High	FG
201	154140050	Gloucester	Pitman Boro	Pitman High	FG
202	294220050	Ocean	Point Pleasant Beach Boro	Point Pleasant Bch High	FG
203	294210030	Ocean	Point Pleasant Boro	Point Pleasant High	FG
204	314230050	Passaic	Pompton Lakes Boro	Pompton Lakes High	FG
205	254365050	Monmouth	Red Bank Regional	Red Bank Reg High	FG
206	354820050	Somerset	Somerville Boro	Somerville High	FG
207	234910050	Middlesex	South Plainfield Boro	South Plainfield High	FG
208	375360020	Sussex	Vernon Twp	Vernon Twp High	FG
209	415465050	Warren	Warren Hills Regional	Warren Hills Reg High Sch	FG
210	155500010	Gloucester	Washington Twp	Washington Twp H S	FG
211	315650040	Passaic	West Milford Twp	West Milford High	FG
212	035830050	Bergen	Wood-Ridge Boro	Wood-Ridge High	FG
213	335910050	Salem	Woodstown-Pilesgrove Reg	Woodstown High	FG
214	255310050	Monmouth	Upper Freehold Regional	Allentown High	GH
215	052610040	Burlington	Lenape Regional	Cherokee High School	GH
216	070800030	Camden	Cherry Hill Twp	Cherry Hill High - East	GH
217	070800040	Camden	Cherry Hill Twp	Cherry Hill High - West	GH
218	251650010	Monmouth	Freehold Regional	Colts Neck High School	GH
219	191050040	Hunterdon	Delaware Valley Regional	Delaware Valley Reg High	GH

	UniqueID	CO_NAME	DIS_NAME	SCH_NAME	DFG
220	231290050	Middlesex	Edison Twp	Edison High	GH
221	031360050	Bergen	Emerson Boro	Emerson Jr Sr High	GH
222	031450050	Bergen	Fair Lawn Boro	Fair Lawn High	GH
223	351610050	Somerset	Franklin Twp	Franklin Twp High	GH
224	251650050	Monmouth	Freehold Regional	Freehold Borough High	GH
225	251650055	Monmouth	Freehold Regional	Freehold Twp High	GH
226	071880050	Camden	Haddon Heights Boro	Haddon Heights Jr-Sr Hs	GH
227	271990050	Morris	Hanover Park Regional	Hanover Park High	GH
228	232150050	Middlesex	Highland Park Boro	Highland Park High	GH
229	211245050	Mercer	East Windsor Regional	Hightstown High	GH
230	251650060	Monmouth	Freehold Regional	Howell High	GH
231	231290053	Middlesex	Edison Twp	J P Stevens High	GH
232	272380020	Morris	Jefferson Twp	Jefferson Twp H	GH
233	395000010	Union	Springfield Twp	Jonathan Dayton High Sch	GH
234	212580040	Mercer	Lawrence Twp	Lawrence High Sch	GH
235	052610050	Burlington	Lenape Regional	Lenape High School	GH
236	372615050	Sussex	Lenape Valley Regional	Lenape Val Regional High	GH
237	032620050	Bergen	Leonia Boro	Leonia High	GH
238	251650070	Monmouth	Freehold Regional	Manalapan High	GH
239	252930050	Monmouth	Manasquan Boro	Manasquan High	GH
240	251650080	Monmouth	Freehold Regional	Marlboro High	GH
241	253160050	Monmouth	Middletown Twp	Middletown H S North	GH
242	253160053	Monmouth	Middletown Twp	Middletown H S South	GH
243	033170050	Bergen	Midland Park Boro	Midland Park High	GH
244	253260050	Monmouth	Monmouth Regional	Monmouth Reg High	GH
245	273370050	Morris	Morris Hills Regional	Morris Hills High	GH
246	273370060	Morris	Morris Hills Regional	Morris Knolls High	GH
247	273335050	Morris	Morris School District	Morristown High	GH
248	273450010	Morris	Mount Olive Twp	Mt. Olive High	GH
249	033930050	Bergen	Paramus Boro	Paramus High	GH
250	273950050	Morris	Parsippany-Troy Hills Twp	Parsippany High	GH
251	273950053	Morris	Parsippany-Troy Hills Twp	Parsippany Hills High	GH
252	274080050	Morris	Pequannock Twp	Pequannock Twp High	GH
253	234130050	Middlesex	Piscataway Twp	Piscataway Twp High	GH
254	274560050	Morris	Roxbury Twp	Roxbury High	GH
255	034600050	Bergen	Rutherford Boro	Rutherford High	GH
256	194890050	Hunterdon	South Hunterdon Regional	S Hunterdon Reg High	GH
257	052610070	Burlington	Lenape Regional	Seneca High School	GH
258	052610060	Burlington	Lenape Regional	Shawnee High School	GH
259	254760050	Monmouth	Shore Regional	Shore Reg High	GH

	UniqueID	CO_NAME	DIS_NAME	SCH_NAME	DFG
260	035150050	Bergen	Teaneck Twp	Teaneck Sr High	GH
261	035410030	Bergen	Waldwick Boro	Waldwick High	GH
262	255420050	Monmouth	Wall Twp	Wall High	GH
263	315570055	Passaic	Wayne Twp	Wayne Hills High	GH
264	315570050	Passaic	Wayne Twp	Wayne Valley High	GH
265	135680050	Essex	West Orange Town	West Orange High	GH
266	035755050	Bergen	Westwood Regional	Westwood Junior/Senior Hs	GH
267	271990070	Morris	Hanover Park Regional	Whippany Park High	GH
268	354815020	Somerset	Somerset Hills Regional	Bernards High	I
269	350555005	Somerset	Bridgewater-Raritan Reg	Brdgwtr-Raritn High Sch	I
270	130760050	Essex	Cedar Grove Twp	Cedar Grove High	I
271	212280030	Mercer	Hopewell Valley Regional	Central High	I
272	134900030	Essex	South Orange-Maplewood	Columbia Sr High	I
273	390980030	Union	Cranford Twp	Cranford Sr High	I
274	030990040	Bergen	Cresskill Boro	Cresskill High School	I
275	131750050	Essex	Glen Ridge Boro	Glen Ridge High	I
276	390310005	Union	Berkeley Heights Twp	Governor Livingston H S	I
277	352170030	Somerset	Hillsborough Twp	Hillsborough High	I
278	252230020	Monmouth	Holmdel Twp	Holmdel High School	I
279	192300050	Hunterdon	Hunterdon Central Reg	Hunterdon Central High	I
280	034300030	Bergen	Ramapo-Indian Hill Reg	Indian Hills High	I
281	130660050	Essex	Caldwell-West Caldwell	James Caldwell High Sch	I
282	272460050	Morris	Kinnelon Boro	Kinnelon High	I
283	132630050	Essex	Livingston Twp	Livingston Sr. High	I
284	272870050	Morris	Madison Boro	Madison High	I
285	032900050	Bergen	Mahwah Twp	Mahwah High School	I
286	233120050	Middlesex	Metuchen Boro	Metuchen High	I
287	133310050	Essex	Montclair Town	Montclair High	I
288	273340010	Morris	Montville Twp	Montville High	I
289	053360040	Burlington	Moorestown Twp	Moorestown High	I
290	033710050	Bergen	Northern Valley Regional	N Valley Reg H Demarest	I
291	033710060	Bergen	Northern Valley Regional	N Valley Reg H Old Tappan	I
292	393560050	Union	New Providence Boro	New Providence High	I
293	193660050	Hunterdon	N Hunt/Voorhees Regional	North Hunterdon Reg High	I
294	033940050	Bergen	Park Ridge Boro	Park Ridge High	I
295	033960040	Bergen	Pascack Valley Regional	Pascack Hills High	I
296	033960050	Bergen	Pascack Valley Regional	Pascack Valley High	I
297	214255050	Mercer	Princeton Regional	Princeton High	I
298	034300050	Bergen	Ramapo-Indian Hill Reg	Ramapo High	I

	UniqueID	CO_NAME	DIS_NAME	SCH_NAME	DFG
299	034310050	Bergen	Ramsey Boro	Ramsey High	I
300	274330050	Morris	Randolph Twp	Randolph High	I
301	033305050	Bergen	River Dell Regional	River Dell Regional H S	I
302	215510030	Mercer	Robbinsville Twp	Robbinsville High School	I
303	394670050	Union	Scotch Plains-Fanwood Reg	Scotch Plains Fanwood Hs	I
304	234860050	Middlesex	South Brunswick Twp	South Brunswick High	I
305	374960050	Sussex	Sparta Twp	Sparta High School	I
306	395090050	Union	Summit City	Summit Sr High	I
307	035160050	Bergen	Tenafly Boro	Tenafly High	I
308	135370050	Essex	Verona Boro	Verona High	I
309	193660060	Hunterdon	N Hunt/Voorhees Regional	Voorhees High	I
310	355550050	Somerset	Watchung Hills Regional	Watchung Hills Reg H	I
311	135630050	Essex	West Essex Regional	West Essex High	I
312	275660030	Morris	West Morris Regional	West Morris Central High	I
313	275660050	Morris	West Morris Regional	West Morris Mendham High	I
314	395730050	Union	Westfield Town	Westfield Senior High	I
315	270785010	Morris	Sch Dist Of The Chathams	Chatham High	J
316	031760050	Bergen	Glen Rock Boro	Glen Rock High	J
317	071900050	Camden	Haddonfield Boro	Haddonfield Memorial High	J
318	133190050	Essex	Millburn Twp	Millburn Sr High	J
319	353320030	Somerset	Montgomery Twp	Montgomery High	J
320	273460050	Morris	Mountain Lakes Boro	Mountain Lakes High	J
321	033700050	Bergen	Northern Highlands Reg	Northern Highlands Reg H	J
322	350350050	Somerset	Bernards Twp	Ridge High	J
323	034390050	Bergen	Ridgewood Village	Ridgewood High	J
324	254580050	Monmouth	Rumson-Fair Haven Reg	Rumson Fair Haven Reg H	J
325	215715025	Mercer	W Windsor-Plainsboro Reg	Wwindsor-Plainsboro North	J
326	215715020	Mercer	W Windsor-Plainsboro Reg	Wwindsor-Plainsboro South	J

Appendix B. Summary of Major Findings from Hierarchical Regressions

HSPA Subject & Dependent Variable	Variables & Significance	Sig. Variables & Standardized Beta's*	Adjusted R^2 (% of Variance Explained by the Model)	SCHDAYL *p*-value
MA TP+AP	SES (.000) G11attend (.000) SCHDAYL (.000)	SES (-.55) G11attend (.41) SCHDAYL(.14)	69.3% * (Model 3)	Statistically significant (.000)
MA TPReflect*	SES (.000) G11attend (.000) SCHDAYL (.000) MA+ (.003) DIS (.255)	SES (.50) G11attend (-.30) SCHDAYL (-.23) MA+ (-.12) DIS (.04)	58.7% (Model 5)	Statistically significant (.000)
LA TP+AP	G11attend (.000) SES (.000) DIS (.040) FMOBILITY (.026) FATTEND (.057)	G11attend (.58) SES (-.38) DIS (-.07) FMOBILTY (.07) FATTEND (-.07)	68.5% (Model 5)	Not statistically significant (.151)
LA TPLA_Reflext*	SES (.000) G11attend (.000) SCHDAYL (.000) DIS (.000) MA+ (.010) enrG9to12 (.037)	SES (.46) G11attend (-.33) SCHDAYL (-.18) DIS (.15) MA+ (-.10) enrG9to12 (-.08)	64.0% (Model 6)	Statistically significant (.000)

*Note: Regressions with transformed dependent variables have standardized Betas whose signs are opposite. A negative Beta value means that the associated predictor variable has a positive relationship with the HSPA passing percentage similarly a negative Beta value means that the predictor variable has a positive relationship with the HSPA passing percentage.

The fact that the adjusted *R* square value for the final hierarchical MA model with the untransformed dependent variable is about 11 percentage points higher than that for the final hierarchical MA model with the transformed dependent variable (69.3% vs. 58.7%) suggests that the regression model using the untransformed dependent variable is superior to (in the sense that it has more predictive power) than the regression model using the transformed variable.

Appendix C: Influence of the Length of the School Day by SES Category

SES Category	MA SCHDAYL Short to Med Range =347-397 Median=390	MA SCHDAYL Med to Long Range=398-415 Median= 406	MA SCHDAYL Short to Long Range= 416-515 Median=435	LA SCHDAYL Short to Med Range =347-397 Median=390	LA SCHDAYL Med to Long Range=398-415 Median= 406	LA SCHDAYL Short to Long Range= 416-515 Median=435
Poor (Mean SES =59.9%)	0.14	5.75	5.89	-2.48	3.35	0.87
Med (Mean SES =19%)	0.84	0.30	0.14	-0.43	-0.60	-1.02
Rich (Mean SES =19%)	1.98	0.59	2.56	0.22	-0.70	-0.49